ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

MSc THESIS

Shahaboddin DANESHVAR

PREDICTION OF UPPER BODY POWER AND MAXIMAL OXYGEN UPTAKE OF CROSS-COUNTRY SKIERS USING DIFFERENT REGRESSION METHODS

DEPARTMENT OF COMPUTER ENGINEERING

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We certify that the thesis titled above was reviewed and approved for the award of degree of the Master of Science by the board of jury on 04/08/2014

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ABSTRACT

MSc THESIS

PREDICTION OF UPPER BODY POWER AND MAXIMAL OXYGEN UPTAKE OF CROSS-COUNTRY SKIERS USING DIFFERENT REGRESSION METHODS

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Upper body power (UBP) and maximal oxygen uptake (VO_2max) are the two most important determinants of cross-country ski race performance. Although numerous studies exist to measure UBP of cross-country skiers, to date, no study has attempted to predict UBP of cross-country skiers. The purpose of this thesis is to develop prediction models for estimating 10-second UBP (UBP_{10}), 60-second UBP (UBP_{60}) and VO_2max of cross-country skiers using different regression methods, namely support vector machines using the radial-basis function (SVM-RBF), linear SVM (SVM-Linear), multi layer perceptron (MLP) and multiple linear regression (MLP). Several UBP and VO_2max prediction models have been developed using different data sets and combination of the predictor variables such as protocol, age, gender, height, weight, body mass index (BMI), heart rate (HR), heart rate at lactate threshold (HRLT) and exercise time. By using 10-fold cross-validation on the data sets, the performance of the models has been evaluated by calculating their standard error of estimates (*SEE*'s) and multiple correlation coefficients (*R*'s). The results show that SVM-RBF-based UBP and VO_2max prediction models perform better (i.e. yield lower *SEE*'s and higher *R*'s) than the prediction models developed by other regression methods.

Key Words: Support Vector Machines, Multilayer Perceptron, Upper Body Power

ÖZ

YÜKSEK LİSANS TEZİ

FARKLI REGRESYON YÖNTEMLERİ KULLANARAK KROS KAYAKÇILARDA ÜST VÜCUT GÜCÜNÜN TAHMİN EDİLMESİ

Shahaboddin DANESHVAR

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Üst vücut gücü (UBP) ve maksimal oksijen alımı (VO_2max) kros kayakçıların yarış performansını belirleyen en önemli iki bileşendir. Kros kayakçıların UBP'sini ölçmek için bir çok çalışma yapılmış olmasına rağmen, şu ana kadar kros kayakçıların UBP'sini tahmin etmek için hiç bir çalışma yapılmamıştır. Bu tezin amacı, radyal tabanlı fonksiyon kullanan destek vektör makineleri (SVM-RBF), doğrusal SVM, çok katmanlı algılayıcı (MLP) ve çoklu doğrusal regresyon (MLP) gibi farklı regresyon yöntemleri kullanarak kros kayakçıların 10 saniye UBP (UBP_{10}), 60 saniye UBP (UBP_{60}) ve VO_2max'larını belirlemek için tahmin modelleri geliştirmektir. Farklı veri setleri ve protokol, yaş, cinsiyet, boy, kilo, vücut kitle indeksi (BMI), kalp atım hızı (HR), laktat eşiğindeki kalp atım hızı (HRLT) ve egzersiz süresi değişkenlerinin kombinasyonları ile bir çok UBP ve VO_2max tahmin modeli oluşturulmuştur. Veri setleri üzerinde 10 katlı çapraz doğrulama kullanarak, modellerin performansı standart tahmin hatası (*SEE*) ve çoklu korelasyon katsayısı (*R*) hesaplanarak değerlendirilmiştir. Elde edilen sonuçlar, SVM-RBF yöntemiyle geliştirilen UBP ve VO_2max tahmin modellerinin diğer regresyon yöntemleri ile geliştirilen tahmin modellerine göre daha performanslı (daha düşük *SEE* ve daha yüksek *R*) olduğunu göstermiştir.

Anahtar Kelimeler: Destek Vektör Makineleri, Çok Katmanlı Algılayıcı, Üst Vücut Gücü

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LIST OF ABBREVIATIONS

AVO_2max	:	Absolute Maximum Oxygen Uptake
BMI	:	Body Mass Index
FEV	:	Forced Expiratory Volume
HR	:	Heart Rate
HRLT	:	Heart Rate at Lactate Threshold
MLP	:	Multilayer Perceptron
MLR	:	Multi Linear Regression
R	:	Multiple Correlation Coefficient
RBF	:	Radial Basis Function
RVO_2max	:	Relative Maximum Oxygen Uptake
SD	:	Standard Deviation
SEE	:	Standard Error of Estimation
SVM	:	Support Vector Machine
UBP	:	Upper Body Power
UBP_{10}	:	10-second Upper Body Power
UBP_{60}	:	60-second Upper Body Power
UBS	:	Upper Body Strength
VO_2max	:	Maximum Oxygen Uptake
UBP-set1	:	Upper Body Power – Data Set 1
UBP-set2	:	Upper Body Power – Data Set 2
UBP-set3	:	Upper Body Power – Data Set 3
UBP-set4	:	Upper Body Power – Data Set 4
VO_2max-set1	:	Maximum Oxygen Uptake – Data Set 1
VO_2max-set2	:	Maximum Oxygen Uptake – Data Set 2
VO_2max-set3	:	Maximum Oxygen Uptake – Data Set 3
VO_2max-set4	:	Maximum Oxygen Uptake – Data Set 4

1. INTRODUCTION

1.1. Cross-Country Skiing

The sport of cross-country skiing is thought to have originated over 4000 years ago in northern Europe. As an endurance sport, cross-country skiing is one of the most difficult sports that burn the most calories per hour of execution. Cross-country skiing is a low-impact exercise that strengthens the upper and lower body. It can also improve the cardiovascular fitness, lower the blood pressure, and assist with weight loss and stress management (Carlsson, 2012).

Cross-country ski racing consisted only of the classical style, in which the skis remain parallel to each other. In this style of skiing, the skier strides uphill by springing from one ski to another while pushing with the opposing pole in a motion similar to running. The double pole technique is used while classical skiing in flat terrain; the skier pushes on both poles simultaneously while bending slightly at the waist, which allows assistance by the trunk muscles. By the mid-1980s, a new skiing style called “skating” had become popular in cross-country ski racing. Ski-skating is a motion similar to ice skating: the skis are turned outward in a V shape, and the skier moves laterally from ski to ski while pushing with both poles. Today, skating and classical races are held as separate events, and most racers participate in both events (Alsobrook, 2005).

1.2. Upper Body Power for Cross-Country Skiers

UBP is an important determinant of cross-country ski race performance. The sport of cross-country skiing requires power to be applied to the poles using the arm, shoulder, and trunk muscles. The ability to apply power during poling is typically referred to as UBP.

One of two methods is typically used to evaluate UBP: criterion measures of UBP, such as a double poling time trial on roller skis, or direct measurement of

power output on an arm ergometer. Performance has typically been defined as average speed or finish time for one or more roller ski or on-snow races or time trials. Points systems based on an entire season of races have also been used.

The need for UBP in cross-country ski racing is a consequence of the use of poles for propulsion. Power generated by the upper body is transmitted through the poles and assists in forward motion. As discussed previously, the upper body is the sole source of power during classical double poling. The upper body may also contribute as much as 50% of the propulsive force during uphill skating and 15% to 30% during uphill classical skiing (Komi, 1987).

Several researchers have concluded that UBP plays an important role in cross-country ski racing. Collectively, these findings indicate that the ability to generate a high UBP is an important determinant of race performance, regardless of whether the power output can be sustained for a few seconds or several minutes.

1.3. Maximal Oxygen Uptake for Cross-Country Skiers

VO_2max is the maximum capacity of an individual's body to transport and use oxygen during incremental exercise, which reflects the physical fitness of the individual. VO_2max is expressed either as an absolute rate in liters of oxygen per minute (L/min) or as a relative rate in milliliters of oxygen per kilogram of body mass per minute (e.g., mL/(kg·min)).

Accurately measuring VO_2max involves a physical effort sufficient in duration and intensity to fully tax the aerobic energy system. In general clinical and athletic testing, this usually involves a graded exercise test (either on a treadmill or on a cycle ergometer) in which exercise intensity is progressively increased while measuring ventilation and oxygen and carbon dioxide concentration of the inhaled and exhaled air. VO_2max is reached when oxygen consumption remains at steady state despite an increase in workload.

However, the direct measurement of VO_2max requires an extensive laboratory and specialized equipment, as well as considerable motivation on the part

of the subject. Consequently, these tests are not suitable for measuring large groups of untrained subjects in a field situation. In addition, such heavy exercise could pose a potential hazard to adults who are not medically cleared or who are exercised without appropriate safeguards or supervision.

As a result, researchers have sought to develop alternative methods that would allow clinicians to predict VO_2max without having to perform direct measurement of oxygen uptake (Acikkar, 2012). More specifically, tests have been devised to predict the VO_2max from performance measures such as walking and running endurance, or from easily obtained heart rates during or immediately after exercise. The tests are easy to administer, can be used with large groups of men or women, and usually require submaximal exercise.

The practical limitations of direct testing have also led to the development of various maximal, submaximal and non-exercise regression models for predicting VO_2max. Submaximal prediction models have certain advantages over maximal tests in that specialized lab equipment is unnecessary, test administrators require less training, and the exercise intensity is realistic for most participants. Submaximal testing is a popular and effective way of evaluating cardiorespiratory fitness and is valuable in developing individualized exercise programs. In addition, periodic submaximal testing provides a convenient way to monitor progress throughout an exercise program and educates participants about their potential risk for cardiovascular and other chronic diseases (Nielson, 2009). Non-exercise methods do not require participants to exercise, and employ questionnaire data in conjunction with other predictor variables such as gender, age, height, body mass and BMI to predict VO_2max. When compared with submaximal and non-exercise models, maximal models give us more accurate results.

In cross-country skiing, success is largely dependent on the body's oxygen uptake ability. The more oxygen that can be delivered to the working muscles, the greater the energy supply, and the faster the body can travel over distance. It is clear that a high maximal oxygen uptake is critical for high level cross country skiing. Cross- country skiers need big aerobic power. Once an athlete has this basic ability other parameters become much more important. The minimum VO_2max range that is

necessary to achieve for international success is 5.5 liters per minute for men, and 3.5 liters per minute for women (Dalleck, 2006).

Although cross-country skiing is an endurance activity which requires a high VO_2max, estimations of required energy output during uphill skiing (made during World Cup competition; by the Finnish biomechanist Pavo Komi) far exceed the highest VO_2max values on record (for humans). The actual estimates approached 150 ml/kg/min and 80 ml/kg/min of oxygen consumption, for uphill and flat skiing, respectively. This means that the power output to climb at race pace must come from both aerobic and short-term anaerobic energy systems. Given that the upper body is a major contributor during climbing and that climbing compromises about 50% of total race time, it should come as no surprise that a short-term maximal double poling power test is a good predictor of ski performance.

1.4. Motivation, Purpose and Contributions of the Thesis

As discussed before, UBP and VO_2max are the most two important factors that affect the performance of a cross-country skier during a race. Therefore, it is important to assess the UBP and VO_2max of a skier. Although several measurement techniques are available to determine the UBP and VO_2max of skiers and these techniques give the most accurate results, there still exist some disadvantages of direct measurement. Direct measurement of UBP and VO_2max requires costly laboratory equipment, trained staff, medical supervision in case of undesired situations and is time-consuming.

MLR has been widely used in past studies for VO_2max prediction. Recently, Akay et al. (Akay, 2014) showed that machine learning methods such as SVM and MLP perform better than MLR for prediction of VO_2max. To the best of our knowledge, there is no single study in literature that aims to predict UBP of cross-country skiers.

In this thesis, we propose to predict UBP_{10}, UBP_{60} and VO_2max of cross-country skiers using different regression methods; namely SVM-RBF, MLP, SVM-Linear and MLR. Four different data sets have been utilized for prediction of UBP_{10}

and UBP_{60}, whereas two data sets have been used for prediction of VO_2max. The predictor variables that appear in the first data set (UBP-set1) is gender, age, weight, height, exercise time, VO_2max and heart rate. The predictor variables that appear in the second data set (UBP-set2) are gender, age, body mass index (BMI), exercise time, VO_2max and heart rate. The predictor variables in the third data set (UBP-set3) are protocol, gender, age, weight, height, exercise time, VO_2max and heart rate. The predictor variables in the fourth data set (UBP-set4) are protocol, gender, age, BMI, exercise time, VO_2max and heart rate. The predictor variables in the fifth data set (VO_2max-set1) are gender, age, weight, height, exercise time, heart rate and heart rate at lactate threshold. The predictor variables in the sixth data set (VO_2max-set2) are gender, age, BMI, exercise time, heart rate and heart rate at lactate threshold. The predictor variables in the seventh data set (VO_2max-set3) are protocol, gender, age, weight, height, exercise time, heart rate and heart rate at lactate threshold. The predictor variables in the eighth data set (VO_2max-set4) are protocol, gender, age, BMI, exercise time, heart rate and heart rate at lactate threshold. Several different models have been developed to predict UBP_{10}, UBP_{60} and VO_2max of cross-country skiers using the mentioned regression methods. The performance of the prediction models has been evaluated by calculating *R*'s and *SEE*'s. 10-fold cross validation has been applied to increase the reliability of the presented results. The results show that SVM-RBF shows the best performance whereas MLR shows the worst performance for prediction of UBP_{10}, UBP_{60} and VO_2max of cross-country skiers.

The main contributions of this thesis are as follows:

1. It is the first study in literature to propose prediction of UBP_{10} and UBP_{60} of cross-country skiers.
2. Application of several different regression methods for UBP and VO_2max prediction allows ranking of the performance of the methods. In this sense, it is shown that SVM-RBF outperforms the other regression methods for prediction of UBP and VO_2max.
3. Prediction of UBP_{10} and UBP_{60} with acceptable error rates is feasible

using the appropriate regression method and predictor variables. It is shown that the *SEE* for prediction of UBP_{10} as well as UBP_{60} is the lowest when SVM-RBF is used along with the predictor variables age, gender, height, weight and VO_2max.

4. It is shown that error rates regarding the prediction of UBP_{60} is always less than the error rates regarding the prediction of UBP_{10}.
5. Using the variables height and weight instead of BMI decreases the error rates for the prediction of UBP_{10} and UBP_{60}.
6. The data sets used in past studies that deal with UBP of cross-country skiers have limited number of subjects (up to 20-25 subjects). In this thesis, larger and different data sets (57 subjects in UBP–set1 and UBP–set2, 79 subjects in UBP–set3 and UBP–set4) have been used, which increases the reliability of the presented results.

1.5. Previous Works

1.5.1. Upper Body Power of Cross-Country Skiers

Ng et al. (Ng, 1988) tested forty-three male citizen or recreational cross-country ski racers to determine their weight and percent body fat, VO_2max, quadriceps, hamstrings (Ham) and upper body (UBS) isokinetic strength, and Quad endurance. In addition, skiers filled out a questionnaire to determine their skiing experience and to see what other activities they participated in. All these variables were run through a stepwise regression procedure to see which characteristics best predicted performance in a 10 km recreational cross-country ski race. The relatively high VO_2max of 56.6 ml O2/kg/min and low body fat of 10.1% indicate this group to be a very fit subset of the general population. All the skiers were active in other sports on a year-round basis. Of the variables studied, UBS, VO_2max, and quadriceps strength were all significant determinants of 10 km race performance, yielding a multiple *R* of 0.78. Quad endurance, Ham strength, weight, body fat, and experience did not significantly contribute toward the prediction of performance. It is felt that a

proper training program for the citizen skier should strive to maximize upper body strength as well as one's aerobic capacity.

Gaskill et. al (Gaskill, 1999) evaluated relationships between UBP and cross-country ski skating race velocity in a cross sectional representation of cross-country skiers. Additionally, cross-country skiers' UBP was compared to UBP of distance runners. Participants were tested on a Street Arm Ergometer for UBP using a ramped maximal UBP test simulating a double poling motion. A strong relationship between UBP and race velocity in skiers was determined. High school skiers were separated into slow and fast groups based on reported race velocity; significant differences in both UBP was found to be an effective partial predictor of race velocity, independent of gender. Mean UBP for the cross-country runners was 46% of mean UBP for the cross-country skiers. With UBP contributing so much to performance in cross-country ski racing, it is recommended that cross-country skiers focus a large portion of their training on the specific development of that fitness component.

Nesser et al. (Nesser, 2004) evaluated four commonly used training methods (weight, circuit, rollerboard, and ski-specific training) for the development of UBP in junior cross-country skiers. Fifty-eight adolescent cross-country skiers were assigned to one of the UBP training methods for a 10-week training program. Fourteen cross-country runners served as controls. Skiers were evaluated pre- and post-training for upper body strength (UBS) using a 10 repetition maximum rollerboard test, for UBP using a double-poling ergometer and for upper body endurance (UBE) with a 3-km, arms-only, rollerski endurance time trial. Competitive race results were collected during the winters before and after training as were all training data. Only the rollerboard training group improved significantly greater than the control group in UBP and UBS. Improvements in UBP, UPS, and UBE were significantly related to improvements in competitive performance. These data suggest that training using a rollerboard with 5-12 repetition maximum and explosive speed is more effective in developing UBP than other common training methods for adolescent cross-country skiers. The practical importance of these data was verified by the significant relationships between improvements in UBP, UBS, and UBE related to improvements in competitive race performance.

Nathan et al. (Nathan, 2005) attained to determine whether increased pole stiffness corresponds with higher measures of UBP in competitive cross-country skiers. Fifteen elite/college level cross-country ski racers tested UBP on a custom-built double-poling ergometer. Ski poles tested were two models of the same brand with different factory-specified stiffness ratings. Subjects underwent three 10 s UBP tests and one 60 s UBP test for each pole type. UBP measures were defined as the average power output over the length of each test. Video recordings of the 10 s and 60 s tests were analyzed with digital imaging software to determine the maximum bend angle for each pole type. These findings suggest that only skiers with highest power output will be able to create enough pole bending to affect measures of UBP between poles with slight differences in stiffness.

Nathan et al. (Nathan, 2005) evaluated the relationship between UBP and classical cross-country ski race performance. A group of experienced skiers completed 3 laboratory tests of UBP on a custom-built double poling ergometer: a 10-second test, a 60-second test, and an incremental test to exhaustion lasting 240-630 seconds. All subjects also competed in the West Yellowstone NorAm race on November 26, 2004. Unfortunately, the small subject number precluded any significant analysis of these data. A second group of skiers completed the same laboratory testing procedure and competed in the West Yellowstone Spam Cup race on December 11, 2004. Pearson's product-moment correlation coefficients were calculated between average race speed and average UBP_{10}, average UBP_{60}, peak power output achieved during the incremental test (W_{peak}), and peak oxygen uptake during the incremental test (VO_{2peak}). After removal of 2 male subjects from the analysis, all 4 measures were found to correlate significantly with race speed. W_{peak} relative to bodyweight showed the highest correlation with race speed. When data was analyzed separately by gender, relative UBP_{10} was the best predictor of RS for women and absolute UBP_{10} was the best predictor of race speed for men. UBP_{10} and UBP_{60} were highly correlated with W_{peak} for all subjects in both groups. Regression analysis also indicated that a 5% improvement in relative W_{peak} could decrease race time by as much as 39 seconds in a 10-km classical race. These findings suggest that both long and short term UBP are important for classical race performance, and that

the factors determining short term UBP may be identical to those determining long term UBP.

Holmber et al. (Holmber, 2007) divided thirty-eight competitive cross-country skiers into three groups to assess the reliability and validity of a new double poling ergometer. Group A performed two maximal 60-s tests, Group B repeated peak oxygen uptake tests on the double poling ergometer, and Group C performed a maximal 6-min test on the double poling ergometer and a double poling time-trial on snow. The power at the poles was 50–70% higher than that at the flywheel. There was a high test–test reliability in the two 60-s power output tests (coefficient of variation = 3.0%) and no significant difference in peak oxygen uptake in the two 6-min all-out tests (coefficient of variation = 2.4%). There was a strong correlation between the absolute and relative power output in the 6-min double poling ergometer test and the double poling performance on snow. In conclusion, the results show that the double poling ergometer has both high reliability and validity.

Nathan et al. (Nathan, 2008) evaluated the relationship between short (60 s) and long duration (4–12 min) measures of UBP and mass start classical cross-country ski performance. Several experienced skiers completed three separate tests of UBP on a double poling ergometer: two tests of highest average power output for UBP_{10} and UBP_{60}, and an incremental test to exhaustion to measure VO_{2peak} and UBP_{peak}. Lastly, subjects competed in a 10-km classical cross-country ski race from which race speed was computed. Race speed correlated highly with UBP_{10}, UBP_{60} and UBP_{peak}; the correlation was lower but still significant for VO_{2peak}. These findings suggest that both short and long duration measures of UBP are important determinants of mass start classical ski race performance.

Carlsson et al. (Carlsson, 2012) established the most appropriate allometric model to predict mean skiing speed during a double-poling roller skiing time-trial using scaling of upper-body power output. Forty-five Swedish junior cross-country skiers of national and international standard were examined. Performance data were subsequently obtained from a 2-km time-trial, using the double-poling technique, to establish mean roller skiing speed. A proportional allometric model was used to predict skiing speed. The results in this study suggest that allometric scaling of

upper-body power output is preferable for the prediction of performance of junior cross-country skiers rather than absolute expression or simple ratio-standard scaling of upper-body power output.

Daneshvar et al. (Daneshvar, 2013) predicted UBP_{10} using a multi-layer feed-forward artificial neural network (MFANN). The data set includes data of 57 subjects. Gender, age, body mass, maximum heart rate, absolute maximum oxygen uptake (AVO_2max), relative maximum oxygen uptake (RVO_2max) and exercise time are predictor variables and UBP_{10} is the target variable. Twelve prediction models have been developed by using combination of the predictor variables. The optimal values of the parameters that affect the performance of the MFANN models (i.e. number of neurons in the hidden layer, learning rate and momentum) have been found by trial and error. By using 10-fold cross-validation on the data set, the performance of the models has been evaluated by calculating their *SEE's* and *R*. The results show that the model including the predictor variables gender, age, body mass and maximum heart rate yields the lowest *SEE* (*SEE* = 24.74) whereas the model including the variables gender, age, body mass and time yields the highest *SEE* (*SEE* = 33.06) for prediction of UBP.

Daneshvar et al. (Daneshvar, 2014) predicted UBP_{10} and UBP_{60} of cross-country skiers using SVM. The dataset includes data of 57 subjects. Gender, age, body mass, height, maximum heart rate, RVO2max and exercise time are predictor variables and UBP_{10} and UBP_{60} are the target variables. Seven different SVM models have been developed by using combination of the predictor variables to predict UBP_{10} and UBP_{60}. The optimal values of the parameters that affect the performance of the SVM models have been found by using grid search. By using 10-fold cross-validation on the data set, the performance of the models has been evaluated by calculating their root mean square errors and *R*'s. The results of SVM models are compared with the ones obtained by MLR. The results show that SVM models outperform MLR models, and can be used safely for prediction of UBP of cross-country skiers.

1.5.2. Maximum Oxygen Uptake for Cross-Country Skiers

Berg (Bergh, 1987) studied the influence of body weight on the performance in cross-country skiing by: dimensional analysis of the ratio (*R*) between the factors of importance to power production (VO_2max, acceleration of gravity) and the braking powers, e.g., friction and air resistance; measuring the energy cost of level skiing; comparing male world class skiers with less successful ones and female winners of the National Championships with non-winners in regard to the relationship between body weight and VO_2max. The dimensional analysis revealed that *R* was less than unity for rather steep uphills. For level, downhill, and less steep uphill skiing, *R* was greater than unity. Thus, skiers who are light will be favored in steep uphill slopes, whereas heavier skiers have advantages in the other parts of the track. Energy cost per kilogram for level skiing was inversely related to the transported mass. Per unit of distance, this cost was positively related to velocity. The world class skiers displayed significantly greater VO_2max than the less successful ones, regardless of the unit used. The lowest standard deviation among the world class skiers was attained when expressing VO_2max as ml min^{-1} $kg^{-2/3}$. The present results indicate that R will be quite close to unity and therefore the performance capability would theoretically be independent of body mass. Furthermore, VO_2max is preferably expressed as ml min^{-1} $kg^{-2/3}$ for cross-country skiers.

Bilodeau et. al (Bilodeau, 1995) evaluated the VO_2max during treadmill running and double-poling with a ski ergometer twice during the competitive season. A progressive double-poling power test was also performed to measure maximal power output. Athletes were then divided into two subgroups according to whenever they had their peaking period early (December-January) or late (March-April) during the season. Skiers peaking early had significantly higher values for all measurements during the upper-body VO_{2peak} test in December compared to April. Values for the upper-body VO_{2peak} test of the skiers peaking late significantly increased from December to April, in accordance with their fitness state. Furthermore, results of the UBP test showed that there was no difference for the skiers peaking early for both

testing periods, while power output increased significantly from December to April for the skiers peaking late. Thus specific upper-body tests appear to be more related to the fitness state of cross-country skiers than a running VO_2max test.

The study of Holmberg et al. (Holmberg, 2007) monitored seven international-level cross country skiers performing on a treadmill while running, double poling and diagonal skiing. Static and dynamic lung function tests were performed and oxygen uptake was measured during submaximal and maximal exercise. Lung function variables were only 5–20% higher than reported in sedentary men. Vital capacity was considerably lower than expected from the skiers' VO_2max, but the maximal ventilation followed a linear relationship with VO_2max. None or only a mild desaturation was observed in running, double poling and diagonal skiing. Blood lactate concentration was slightly higher in and diagonal skiing than in double poling but not different from running. In diagonal skiing, VO_2max was 6.23 ± 0.47 L/min, which was 3.8% and 13.9% higher than in running and double poling, respectively, with similar peak heart rates for the three exercise modes. No relationships were present either between the degree of desaturation and pulmonary functions tests, or with peak oxygen uptakes. The low blood lactate accumulation during the exhaustive efforts contributed to the arterial oxygen saturation being mild in spite of the very high oxygen uptake observed in these skiers.

Klusiewicz et al. (Klusiewicz, 2011) assessed the accuracy of prediction of VO_2max from submaximal and maximal exercises on a ski ergometer, which imitated the work of the arms during cross-country skiing. Twenty-seven female and twenty-nine male biathletes and cross-country skiers were investigated. The subjects performed the incremental exercise test on the ski ergometer until volitional exhaustion. VO_2max was determined directly and its predicted values were calculated from the linear relationship between VO_2 and HR in a submaximal exercise extrapolated to the age-predicted HRmax; from the linear relationship between VO_2 and power output at submaximal and maximal exercise; from the linear relationship between VO_2max and VO_2 at HR=170 min^{-1} and from the linear relationship between VO_2max and power output at HR=170 min^{-1}. The differences between measured and predicted VO_2max ranged from 0.3% to 1.2%. Correlation

coefficients between measured and predicted VO_2max ranged from 0.6 to 0.91. Total error ranged from 5.91% to 11.7% and standard estimation error from 5.3% to 11.0%. The results demonstrated that VO_2max can be predicted from the exercise test on the ski ergometer both in the submaximal exercise from the relation between heart rate and oxygen uptake or power output and from the relation between VO_2max and maximal power output without oxygen uptake measurement.

2. OVERVIEW OF REGRESSION METHODS

2.1. Support Vector Machines

Support Vector learning is based on simple ideas which originated in statistical learning theory (Vapnik, 1998). The simplicity comes from the fact that SVMs apply a simple linear method to the data but in a high-dimensional feature space non-linearly related to the input space. Moreover, even though we can think of SVMs as a linear algorithm in a high-dimensional space, in practice, it does not involve any computations in that high-dimensional space. This simplicity combined with state of the art performance on many learning problems (classification and regression) has contributed to the popularity of the SVM.

SVMs use an implicit mapping Φ of the input data into a high-dimensional feature space defined by a kernel function, i.e., a function returning the inner product $(\Phi(x), \Phi(x'))$ between the images of two data points x, x' in the feature space. The learning then takes place in the feature space, and the data points only appear inside dot products with other points. This is often referred to as the "kernel trick" (Schölkopf, 2002). More precisely, if a projection $\Phi: X \rightarrow H$ is used, the dot product $(\Phi(x), \Phi(x'))$ can be represented by a kernel function k

$$k(x, x') = \langle \Phi(x), \Phi(x') \rangle \tag{2.1.}$$

which is computationally simpler than explicitly projecting x and x' into the feature space H.

One interesting property of support vector machines and other kernel-based systems is that, once a valid kernel function has been selected, one can practically work in spaces of any dimension without any significant additional computational cost, since feature mapping is never effectively performed. In fact, one does not even need to know which features are being used.

Another advantage of SVMs and kernel methods is that one can design and use a kernel for a particular problem that could be applied directly to the data without

the need for a feature extraction process. This is particularly important in problems where a lot of structure of the data is lost by the feature extraction process (e.g., text processing).

2.1.1. Classification

In classification, support vector machines separate the different classes of data by a hyperplane

$$\langle \mathbf{w}, \Phi(x) \rangle + b = 0 \tag{2.2.}$$

corresponding to the decision function

$$f(x) = \text{sign}(\langle \mathbf{w}, \Phi(x) \rangle + b) \tag{2.3.}$$

It can be shown that the optimal, in terms of classification performance, hyper-plane (Vapnik, 1998) is the one with the maximal margin of separation between the two classes. It can be constructed by solving a constrained quadratic optimization problem whose solution w has an expansion $\mathbf{w} = \sum_i \alpha_i \Phi(x_i)$ in terms of a subset of training patterns that lie on the margin. These training patterns, called support vectors, carry all relevant information about the classification problem. Omitting the details of the calculation, there is just one crucial property of the algorithm that we need to emphasize: both the quadratic programming problem and the final decision function depend only on dot products between patterns. This allows the use of the "kernel trick" and the generalization of this linear algorithm to the nonlinear case.

In the case of the L2-norm soft margin classification the primal optimization problem takes the form:

$$\begin{aligned} &\text{minimize} \quad t(\mathbf{w}, \xi) = \frac{1}{2} \| \mathbf{w} \|^2 + \frac{C}{m} \sum_{i=1}^{m} \xi_i \\ &\text{subject to } y_i(\langle \Phi(x_i), \mathbf{w} \rangle + b) \geq 1 - \xi_i \quad (i = 1, \dots, m) \\ &\qquad \xi_i \geq 0 \quad (i = 1, \dots, m) \end{aligned} \tag{2.4.}$$

where m is the number of training patterns, and $y_i = \pm 1$. As in most kernel methods, the SVM solution **w** can be shown to have an expansion

$$\mathbf{w} = \sum_{i=1}^{m} \alpha_i \, y_i \Phi \, (x_i) \tag{2.5.}$$

where non-zero coefficients (support vectors) occur when a point (x_i, y_i) meets the constraint. The coefficients α_i are found by solving the following (dual) quadratic programming problem:

$$\begin{aligned} &\text{minimize} && W(\alpha) = \sum_{i=1}^{m} \alpha_i + \frac{1}{2} \sum_{i,j=1}^{m} \alpha_i \alpha_j y_i y_j \, k(x_i, x_j) \\ &\text{subject to} && 0 \le \alpha_i \le \frac{C}{m} \quad (i = 1, \dots, m) \\ & && \sum_{i=1}^{m} \alpha_i y_i = 0. \end{aligned} \tag{2.6.}$$

This is a typical quadratic problem of the form:

$$\begin{aligned} &\text{minimize} && c^T x + \frac{1}{2} x^T H x \\ &\text{subject to} && b \le Ax \le b + r \\ & && l \le x \le u \end{aligned} \tag{2.7.}$$

where $H \in \mathbb{R}^{m \times m}$ with entries $H_{ij} = y_i y_j k(x_i, x_j)$, $C = (1, \dots, 1) \in \mathbb{R}^m$, $u = (C, \dots, C) \in \mathbb{R}^m$, $l = (0, \dots, 0) \in \mathbb{R}^m$, $A = (y_1, \dots, y_m) \in \mathbb{R}^m$, $b = 0$, $r = 0$. The cost parameter *C* of the SVM formulation in Equation 2.7. controls the penalty paid by the SVM for miss-classifying a training point and thus the complexity of the prediction function. A high cost value *C* will force the SVM to create a complex enough prediction function to miss-classify as few training points as possible, while a lower cost parameter will lead to a simpler prediction function. Therefore, this type of SVM is usually called C-SVM.

Another formulation of the classification with a more intuitive hyper parameter than *C* is the ϑ-SVM (Schölkopf, 2000). The ϑ parameter has the interesting property of being an upper bound on the training error and a lower bound

on the fraction of support vectors found in the data set, thus controlling the complexity of the classification function build by the SVM. For multi-class classification, mostly voting schemes such as one-against-one and one-against-all are used. In the one-against-all method k binary SVM classifiers are trained, where k is the number of classes, each trained to separate one class from the rest. The classifiers are then combined by comparing their decision values on a test data instance and labeling it according to the classifier with the highest decision value.

In the one-against-one classification method (also called pair wise classification (Knerr, 1990; Kreßel 1999), $\binom{k}{2}$ classifiers are constructed where each one is trained on data from two classes. Prediction is done by voting where each classifier gives a prediction and the class which is most frequently predicted wins ("Max Wins"). This method has been shown to produce robust results when used with SVMs (Hsu, 2002a). Although this suggests a higher number of support vector machines to train the overall CPU time used is less compared to the one-against-all method since the problems are smaller and the SVM optimization problem scales super-linearly.

2.1.2. Regression

By using a different loss function called the _-insensitive loss function$\| y - f(x) \|_\epsilon = max\{0, \| y - f(x) \| - \epsilon\}$, SVMs can also perform regression. This loss function ignores errors that are smaller than a certain threshold $\epsilon > 0$ thus creating a tube around the true output. The primal becomes:

$$\begin{aligned} &\text{minimize} && t(\boldsymbol{w}, \xi) = \frac{1}{2} \| w \|^2 + \frac{C}{m} \sum_{i=1}^{m} (\xi_i + \xi_i^*) \\ &\text{subject to} && (\langle \Phi(x_i), \mathbf{w} \rangle + b) - y_i \leq \epsilon - \xi_i \end{aligned} \tag{2.8.}$$

$$\begin{aligned} & y_i - (\langle \Phi(x_i), \mathbf{w} \rangle + b) \leq \epsilon - \xi_i^* \\ & \xi_i^* \geq 0 \qquad (i = 1, \ldots, m) \end{aligned} \tag{2.9.}$$

We can estimate the accuracy of SVM regression by computing the scale parameter of a Laplacian distribution on the residuals $\zeta = y - f(x)$, where $f(x)$ is the estimated decision function.

2.1.3. Kernel functions

As seen before, the kernel functions return the inner product between two points in a suitable feature space, thus defining a notion of similarity, with little computational cost even in very high-dimensional spaces. Kernels commonly used with kernel methods and SVMs in particular include the following:

- the linear kernel implementing the simplest of all kernel functions

$$k(\mathrm{x}, \mathrm{x}') = \langle \mathrm{x}, \mathrm{x}' \rangle \tag{2.10.}$$

- the Gaussian Radial Basis Function (RBF) kernel

$$k(\mathrm{x}, \mathrm{x}') = \exp(-\sigma \parallel \mathrm{x} - \mathrm{x}' \parallel^2) \tag{2.11.}$$

- the polynomial kernel

$$k(\mathrm{x}, \mathrm{x}') = (scale. \langle \mathrm{x}, \mathrm{x}' \rangle + offset)^{degree} \tag{2.12.}$$

- the hyperbolic tangent kernel

$$k(\mathrm{x}, \mathrm{x}') = \tanh(scale. \langle \mathrm{x}, \mathrm{x}' \rangle + offset) \tag{2.13.}$$

- the Bessel function of the first kind kernel

$$k(\mathrm{x}, \mathrm{x}') = \frac{Bessel^{n}_{(\vartheta+1)}\,(\sigma \parallel \mathrm{x} - \mathrm{x}' \parallel)}{(\parallel \mathrm{x} - \mathrm{x}' \parallel)^{-n(\vartheta+1)}} \tag{2.14.}$$

- the Laplace Radial Basis Function (RBF) kernel

$$k(\mathrm{x},\mathrm{x}') = \exp(-\sigma \parallel \mathrm{x} - \mathrm{x}' \parallel) \quad (2.15.)$$

- the ANOVA radial basis kernel

$$k(\mathrm{x},\mathrm{x}') = (\sum_{k=1}^{n} \exp(-\sigma(x^k - x'^k)^2))^d \quad (2.16.)$$

- the linear splines kernel in one dimension

$$k(x,x') = 1 + xx' \min(x,x') - \frac{x+x'}{2}(\min(x,x'))^2 + \frac{(\min(x,x'))^3}{3} \quad (2.17.)$$

and for the multidimensional case $k(\mathrm{x},\mathrm{x}') = \prod_{k=1}^{n} k(x^k, x'^k)$.

The Gaussian and Laplace RBF and Bessel kernels are general-purpose kernels used when there is no prior knowledge about the data. The linear kernel is useful when dealing with large sparse data vectors as is usually the case in text categorization. The polynomial kernel is popular in image processing and the sigmoid kernel is mainly used as a proxy for neural networks. The splines and ANOVA RBF kernels typically perform well in regression problems.

2.2. Multilayer Perceptron

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined by the connections between elements. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between the elements. Commonly neural networks are adjusted, or trained,

so that a particular input leads to a specific target output. Such a situation is shown in Figure 2.1. Here, the network is adjusted, based on a comparison of the output and the target, up to the network output matches the target. Typically many such input/target output pairs are used to train a network. Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector. Incremental training is sometimes referred to as ‘‘online’’ or ‘‘adaptive’’ training. Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, and vision and control systems. Today neural networks can be trained to solve problems that are difficult for conventional computer programs or human beings (Saltan, 2008).

Considering the geometry of the network, there are several types of neural networks: Hopfield, Hamming, Campenter and Grossberg, Kohonen, multi-layer feed forward neural network and others (Lippmann, 1987). Neural networks with different geometry are used for solving various problems.

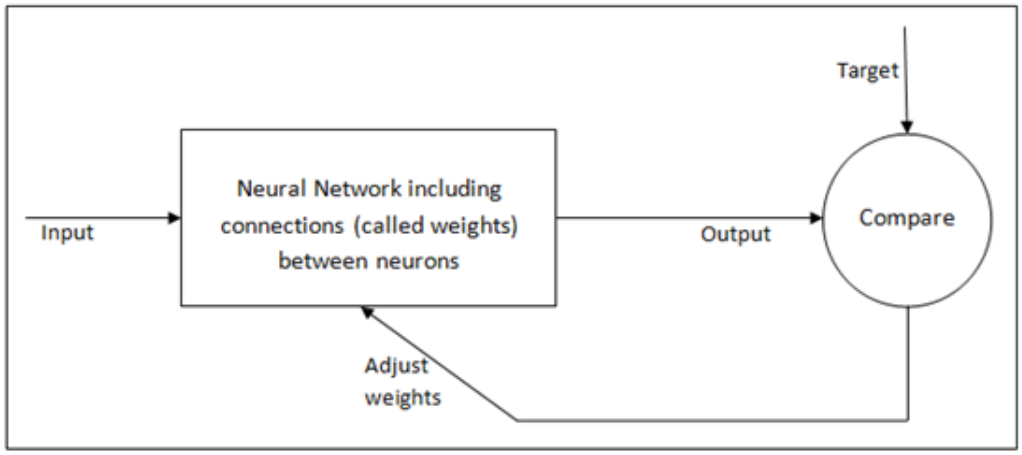


Figure 2.1. Concept of an artificial neural network

The fist three types of neural networks are usually used for binary input data and with problems of classification into classes. The last two types of neural networks are appropriate for the approximation of an unknown function (Ambrozic,

2003).

The geometry of a multilayer feed-forward neural network is shown in Figure 2.2. Input units are connected to the first layer of hidden units which are further connected to the units of the second hidden layer. The units of the last hidden layer are connected to the output units. The input units represent the input data, and the output units represent the output data. The hidden layers may be considered as a black box which performs the necessary transformations of the input data so that the target output data are obtained.

Each unit is represented by its value y_i^k : Each connection between the units is represented by its weight w_{ij}^k ; where index i corresponds to the unit number of the k^{th} layer, while index j corresponds to the unit number of the $(k-1)^{th}$ layer. The input layer is denoted by 0, whereas the output layer is denoted by n_1: The signals travel in one direction only, i.e. from the input layer towards the output layer.

The value of a unit is multiplied by the corresponding weight and added to the value of the signal in the unit of the next layer. In addition, the value of bias neuron or threshold ϑ_i^k is added to the equation, which is given in (2.18) (Ambrozic & Turk, 2003).

$$y_i^k = f\left(\sum_{i=1}^{n_{k-1}} w_{ij}^k y_i^{k-1} + \vartheta_i^k\right) \tag{2.18}$$

Activation function $f(.)$ enables the modeling of an arbitrary nonlinear relation between input and output variables. Different functions could be used as an activation function. The usual choices of activation function are a sigmoid function, Gaussian and radial basis function.

The behavior of the neural network depends on the values of weights w_{ij}^k and thresholds ϑ_i^k which have to be determined by the training procedure. The supervised training is in fact a general optimization problem in which the minimum of error E_p is sought

$$E_p = \frac{1}{2}\sum_{i=1}^{n_0}\left(t_{pi} - y_{pi}^{nl}\right)^2, \tag{2.19}$$

where t_{pi} are the target output values, y_{pi}^{nl} are the values of neurons in the output layer, i.e. the output values evaluated by neural network, n_0 is the number of neurons in output layer, i.e. the number of output variables (Ambrozic, 2003).

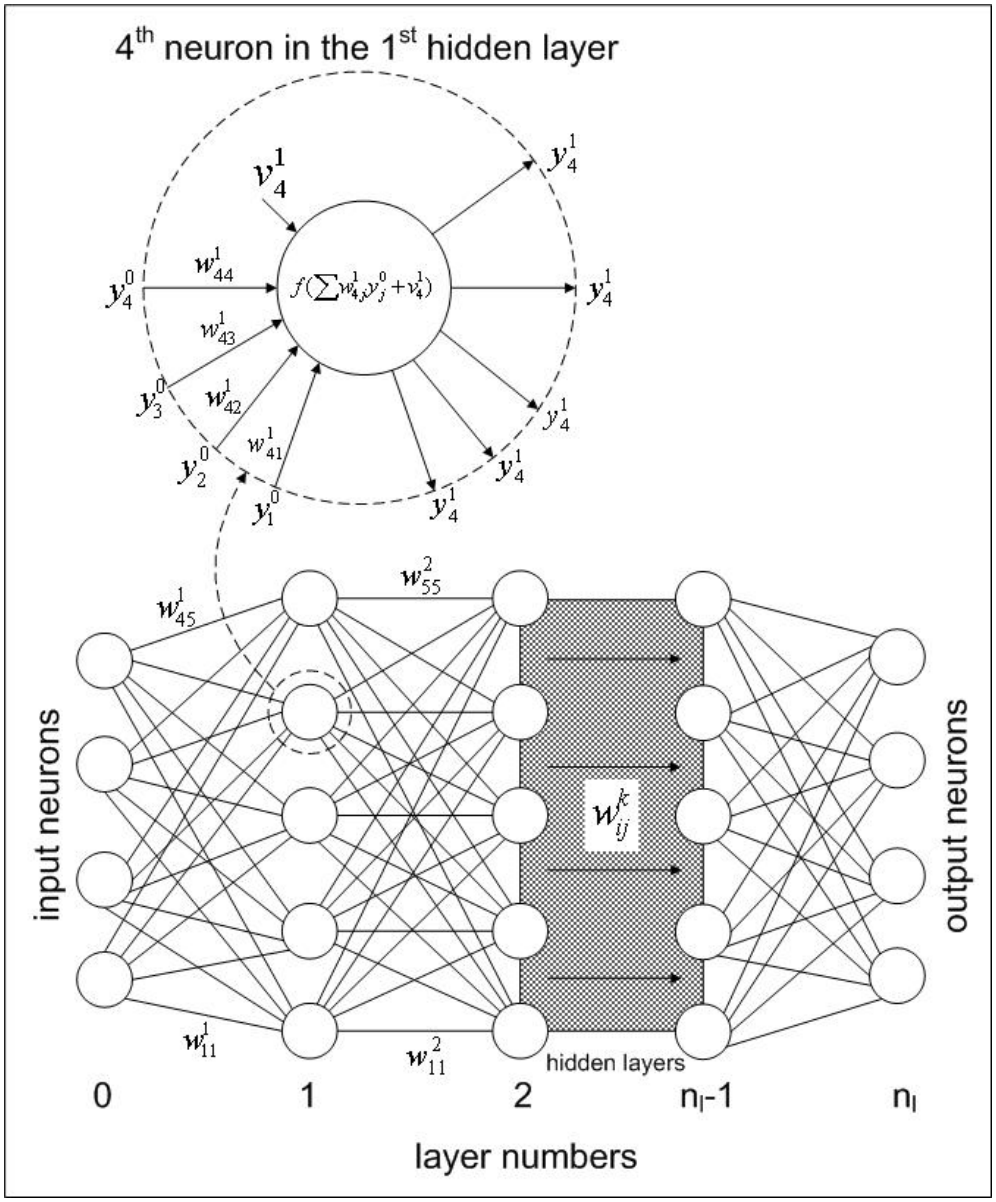


Figure 2.2. Geometry of a multilayer feed-forward neural network

2.3. Multiple Linear Regression (MLR)

The multiple linear regression model is an extension of a simple linear regression model to incorporate two or more explanatory variable in a prediction equation for a response variable. Multiple regression modeling is now a mainstay of statistical analysis in most fields because of its power and flexibility. It requires very little effort (and sometimes even less thought) to estimate very complicated models with large numbers of variables.

When we wish to model a continuous outcome variable, then an appropriate analysis is often multiple linear regression. For simple linear regression we have one continuous input variable. In multiple regression we generalize the method to more than one input variable and we will allow them to be continuous or categorical. Multiple regression is a generalization of the analysis of variance and analysis of covariance.

In multiple regression the basic model is the following:

$$y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ip} + \varepsilon_i \qquad (2.20.)$$

We assume that the error term ε_i is normally distributed, with mean 0 and standard deviation σ. Here y_i is the output for unit or subject *i* and there are *k* input variables $X_{i1}, X_{i2}, \ldots, X_{ip}$. Often y_i is termed the dependent variable and the input variables $X_{i1}, X_{i2}, \ldots, X_{ip}$ are termed the independent variables. The latter can be continuous or nominal. However the term "independent" is a misnomer since the *X*'s need not be independent of each other. Sometimes they are called the explanatory or predictor variables. Each of the input variables is associated with a regression coefficient $\beta_1, \beta_2, \ldots, \beta_k$. There is also an additive constant term β_0. These are the model parameters.

We can write the first section on the right-hand side of equation (2.20.) as

$$LP_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ip} \qquad (2.21.)$$

where LP_i is known as the *linear predictor* and is the value of y_i predicted by the input variables. The difference $y_i - LP_i = \varepsilon_i$ is the error term.

The models are fitted by choosing estimates $b_0, b_1, \ldots, b_p$, which minimize the sum of squares (SS) of the predicted error. These estimates are termed ordinary least squares estimates. Using these estimates we can calculate the fitted values y_i^{fit}, and the observed residuals $e_i = y_i - y_i^{fit}$. Here it is clear that the residuals estimate the error term (Draper, 1998).

Uses of multiple regression can be summarized as follows:

1. To adjust the effects of an input variable on a continuous output variable for the effects of confounders. For example, to investigate the effect of diet on weight allowing for smoking habits. Here the dependent variable is the outcome from a clinical trial. The independent variables could be the two treatment groups (as a 0/1 binary variable), smoking (as a continuous variable in numbers of packs per week) and baseline weight. The multiple regression model allows one to compare the outcome between groups, having adjusted for differences in baseline weight and smoking habit. This is also known as analysis of covariance.
2. To analyze the simultaneous effects of a number of categorical variables on an output variable. An alternative technique is the analysis of variance but the same results can be achieved using multiple regression.
3. To predict a value of an outcome, for given inputs. For example, an investigator might wish to predict the forced expiratory volume (*FEV*1) of a subject given age and height, so as to be able to calculate the observed *FEV*1 as a percentage of predicted, and to decide if the observed *FEV*1 is below, say, 80% of the predicted one.

3. DATA SET GENERATION

3.1. Subjects

Trained cross-country ski racers from the local community with a minimum of 3 years of ski racing experience were recruited for this study. Subjects were primarily collegiate racers from the Montana State University ski team or local adult citizen racers. Ability levels ranged from three subjects who were ranked among the top collegiate skiers in the United States to weekend citizen racers. Prior to participating, all subjects read and signed an informed consent document approved by the Montana State University Institutional Review.

3.2. Testing Procedures

Participation in this study required three visits to the Montana State University Movement Science/Human Performance Laboratory in Bozeman, MT. During the first visit, descriptive information (age, body height and mass) was recorded and subjects completed three trials of a 30-s test followed by a single 60-s test on a custom-built double poling ergometer. Subjects then completed an incremental test to exhaustion on the same ergometer during their second visit. Subjects were instructed to avoid any strength training or high intensity exercise for 48 h prior to either testing session. The first two visits took place within 4 weeks of a local classical ski race, and a minimum of 2 days apart from each other. Body composition, which was used only for descriptive purposes, was estimated during the third visit by hydrostatic weighing.

3.3. 30- and 60-s UBP Tests

After a 5-min warm-up on the double poling ergometer at a self-selected power output, subjects rested for 3 min before performing three consecutive trials of a 30-s test. The skier ramped up power output and poling cadence for the first 20 s of

the test before double poling at maximal effort the final 10 s. The average power output measured by the ergometer during the final 10 s was recorded as the UBP_{10}. Subjects used the first of three trials as a practice and additional warm-up, using approximately 80% population-specific equations (Nathan, 2008).

3.4. Cross-Country Ski Racing

Each subject competed in a 10-km mass start classical cross-country ski race. Subjects were responsible for their own ski equipment, including waxing skis to optimize grip and glide for the snow conditions and weather. Subjects followed their own personal warm-up procedures. Average race speed (RS) was calculated from the course distance and each subject's official race time. The race course consisted of overlapping 6- and 4-km loops over lightly rolling terrain with high and low altitudes of 2,040 and 2,090 m, respectively. Air temperature was approximately 30°F at race start, warming to mid-30s by the finish, with clear skies and no wind. The snow was transformed and granular. No standard grip or glide waxes were used. For grip wax, subjects chose various klisters for moderately warm conditions; specific waxes used by each subject were not recorded. Most skiers self-reported using the double pole or kick double pole techniques for one-half to two-thirds of the race, though a few of the faster finishers reported double poling roughly three-fourths of the race (Nathan, 2008).

It should be acknowledged that the altitude of the testing lab (1,524 m) differed from the ski race venue (2,040– 2,090 m) by just over 500 m. While all subjects were acclimatized to living (1,400–1,600 m) and training (1,500– 2,050 m) at moderate altitudes, it is not known whether all subjects were fully acclimatized to the slightly higher race venue. Given the similarity of the training and race venue altitudes, it was assumed that relationships between the lab-based dependent measures and ski race speed were not influenced.

3.5. Test-Retest Reliability

A separate group of local skiers, all with 3+ years of ski racing experience, participated in two UBP testing visits to the same lab within 24 h to 2 weeks of each other. The purpose of this testing was to evaluate the day-to-day repeat-ability of the UBP_{10} and UBP_{60} test variables. During each test session, both the UBP_{10} and UBP_{60} tests were performed in the same manner as described above. The highest UBP_{10} value over two successful trials within the same test session was recorded for subsequent reliability calculations. Subjects who had never performed these tests prior to this study returned for a third visit (i.e., first visit data were not used for data analysis). Due to scheduling limitations of the skiers, a similar reliability evaluation for the computation of UBP_{PEAK} from the incremental test to exhaustion was not possible.

3.6. Upper Body Power Ergometer

A modified Concept 2 rowing ergometer (Concept 2 Model D, Morrisville, VT, USA), similar to that described by Nils-son et al. (2004), was used for all UBP testing in this study. In place of the sliding seat on a typical Concept 2 ergometer, a resistance-loaded trolley was connected to the chain that turned the air-braked flywheel. Two cross-country ski poles were attached to the trolley such that pushing on the poles slid the trolley backward along the rail. The chain, in turn, spun the ergometer's flywheel which thus provided resistance each time the poles were pushed backward. As the poles were brought back forward during the recovery phase, the trolley was pulled forward by the pole tips along the rail with very little resistance. Additional ergometer modifications included a longer steel rail than a typical rowing ergometer, as well as a platform mounted above and to the front of the rail on which the subject stood during testing. Like the Concept 2 ergometer, the modified ergometer provided a continuous digital display of power output in watts (using the Concept 2 PM3 digital monitor), as well as a recording of average power output over user-defined work periods. Test-retest of power measurements using the

Concept 2 ergometer have been shown to be reliable in tests lasting approximately 90 and 420 s (Soper and Hume 2004). Ski poles for ergometer testing (Toko P232 poles, Mammut Sports Group AG, Seon, Switzerland; Infinity synthetic cork grips and Infinity Vise straps, Zaveral Racing Equipment, Mt Upton, NY, USA), available in 5-cm increments between 135 and 170 cm, were Wt to within 2.5 cm of each subject's own racing pole length.

3.7. Indirect Calorimetry

Oxygen uptake during the incremental test to exhaustion was measured using a TrueMax 2400 metabolic system. Subjects breathed room air through a mouthpiece fitted with one-way valves, which directed expired air into the analyzer module via a length of tubing. The oxygen and carbon dioxide analyzers were calibrated prior to each test using a certified gas mixture, while the system's ventilation measurements were evaluated using a calibrated 3-L syringe (Hans Rudolph, Kansas City, MO, USA). The sample interval for computed VO_2 values was 20 s, while heart rate was recorded every 5-s using a Polar Accurex Plus heart rate monitor (Polar Electro, Inc, Lake Success, NY, USA). Body height and mass were measured to the nearest 0.1 cm and 0.1 kg, respectively using a Health-o-Meter.

Table 3.1. Descriptive statistics of UBP-set1

Variables	**Mean ± Standard Deviation**
Gender	0.474 ± 0.504
Age	18.789 ± 1.998
Weight (kg)	67.719 ± 6.988
Height (cm)	174 ± 8.264
HR (bpm)	195.035 ± 7.263
Exercise Time (sec)	11.791 ± 1.002
VO_2max (ml/kg/min)	63.091± 8.432
UBP_{10} (W)	231.035 ± 73.091
UBP_{60} (W)	177.491± 55.977

Table 3.2. Descriptive statistics of UBP-set2

Variables	**Mean ± Standard Deviation**
Gender	0.474 ± 0.54
Age	18.807 ± 1.986
BMI (kg/m^2)	22.265 ± 1.906
HR (bpm)	194.895 ± 7.242
Exercise Time (sec)	11.78 ± 1.022
VO_2max (ml/kg/min)	63.06 ± 8.485
UBP_{10} (W)	231.035 ± 73.091
UBP_{60} (W)	177.491 ± 55.977

Table 3.3. Descriptive statistics of UBP-set3

Variables	**Mean ± Standard Deviation**
Protocol	2.76 ± 0.43
Gender	0.493 ± 0.503
Age	18.52 ± 2.274
Weight (kg)	67.033 ± 7.137
Height (cm)	174.363 ± 8.223
HR (bpm)	196.48 ±7.522
Exercise Time (sec)	11.541 ± 1.591
VO_2max (ml/kg/min)	62.409 ± 8.411
UBP_{10} (W)	226.24 ± 73.819
UBP_{60} (W)	172.773 ± 55.358

Table 3.4. Descriptive statistics of UBP-set4

Variables	**Mean ± Standard Deviation**
Protocol	2.76 ± 0.43
Gender	0.493 ± 0.503
Age	18.533 ± 2.268
BMI (kg/m^2)	22.059 ± 1.902
HR (bpm)	196.373 ± 7.528
Exercise Time (sec)	11.532 ± 1.599
VO_2max (ml/kg/min)	62.385 ± 8.449
UBP_{10} (W)	226.24 ± 73.819
UBP_{60} (W)	172.773 ± 55.358

Table 3.5. Descriptive statistics of VO_2max-set1

Variables	**Mean ± Standard Deviation**
Gender	0.428 ± 0.497
Age	18.935 ± 2.878
Weight (kg)	66.357 ± 7.809
Height (cm)	173.579 ± 8.363
HR (bpm)	195.514 ± 7.079
HRLT (bpm)	177.384 ± 8.614
Exercise Time (sec)	11.478 ± 1.024
VO_2max (ml/kg/min)	61.54 ± 7.991

Table 3.6. Descriptive statistics of VO_2max-set2

Variables	**Mean ± Standard Deviation**
Gender	0.428 ± 0.497
Age	18.935 ± 2.878
BMI (kg/m^2)	21.969 ± 1.863
HR (bpm)	195.514 ± 7.079
HRLT (bpm)	177.384 ± 8.614
Exercise Time (sec)	11.478 ± 1.042
VO_2max (ml/kg/min)	61.54 ± 7.991

Table 3.7. Descriptive statistics of VO_2max-set3

Variables	**Mean ± Standard Deviation**
Protocol	0.789 ± 0.709
Gender	0.423 ± 0.495
Age	18.743 ± 3.051
Weight (kg)	65.721 ± 7.787
Height (cm)	173.409 ± 8.282
HR (bpm)	196.423 ± 7.367
HRLT (bpm)	179.714 ± 9.595
Exercise Time (sec)	11.487 ± 1.381
VO_2max (ml/kg/min)	60.927 ± 7.892

Table 3.8. Descriptive statistics of VO_2max-set4

Variables	**Mean ± Standard Deviation**
Protocol	0.189 ± 0.409
Gender	0.423 ± 0.495
Age	18.743 ± 3.051
BMI (kg/m^2)	21.806 ± 1.86
HR (bpm)	196.423 ± 7.367
HRLT (bpm)	179.714 ± 9.595
Exercise Time (sec)	11.487 ± 1.381
VO_2max (ml/kg/min)	11.487 ± 1.381

4. RESULTS AND DISCUSSION

As described previously, eight data sets have been used in this study. The first and second data sets include data of 57 subjects. The second and third data sets include data of 75 subjects. The fifth and sixth data sets include data of 138 subjects. The seventh and eighth data sets include data of 175 subjects. Using each data set, several UBP_{10}, UBP_{60} and VO_2max prediction Models have been developed. These models contain various combinations of the predictor variables. For each model UBP_{10}, UBP_{60} and VO_2max have been predicted using SVM-RBF, MLP, SVM-Linear and MLR. Weka 3.6 and its LibSvm library have been used for developing prediction models.

The performance of SVM-RBF, MLP, SVM-Linear and MLR models have been evaluated by using 10-fold cross validation and calculating the *SEE* and *R*, whose formulas are given in (4.1.) and (4.2.), respectively,

$$SEE = \sqrt{\frac{\sum(Y-Y')^2}{N}} \tag{4.1.}$$

$$R = \sqrt{1 - \frac{\sum(Y-Y')^2}{\sum(Y-\bar{Y})^2}} \tag{4.2.}$$

In formulas (4.1.) and (4.2.), Y is the measured value, Y' is the predicted value, $\bar{Y}$ is the mean of the measured values and N is the number of samples in a test subset.

Table 4.1 shows the prediction models for UBP and predictor variables that each model contains whereas Table 4.2 shows the prediction models for VO_2max and predictor variables that each model contains.

Table 4.1. Overview of UBP_{10} and UBP_{60} models along with their predictor variables.

Models	**Predictor Variables**
Model 1 and 8	Age, gender, height, weight, VO_2max
Model 2 and 9	Age, gender, height, weight, HR
Model 3 and 10	Age, gender, height, weight, time
Model 4 and 11	Age, gender, height, weight, VO_2max, HR
Model 5 and 12	Age, gender, height, weight, time, VO_2max
Model 6 and 13	Age, gender, height, weight, time, HR
Model 7 and 14	Age, gender, height, weight, time, VO2max, HR
Model 15 and 22	Age, gender, BMI, VO_2max
Model 16 and 23	Age, gender, BMI, HR
Model 17 and 24	Age, gender, BMI, time
Model 18 and 25	Age, gender, BMI, VO_2max, HR
Model 19 and 26	Age, gender, BMI, time, VO_2max
Model 20 and 27	Age, gender, BMI, time, HR
Model 21 and 28	Age, gender, BMI, time, VO2max, HR
Model 29 and 36	Protocol, age, gender, height, weight, VO_2max
Model 30 and 37	Protocol, age, gender, height, weight, HR
Model 31 and 38	Protocol, age, gender, height, weight, time
Model 32 and 39	Protocol, age, gender, height, weight, VO_2max, HR
Model 33 and 40	Protocol, age, gender, height, weight, time, VO_2max
Model 34 and 41	Protocol, age, gender, height, weight, time, HR
Model 35 and 42	Protocol, age, gender, height, weight, time, VO2max, HR
Model 43 and 50	Protocol, age, gender, BMI, VO_2max
Model 44 and 51	Protocol, age, gender, BMI, HR
Model 45 and 52	Protocol, age, gender, BMI, time
Model 46 and 53	Protocol, age, gender, BMI, VO_2max, HR
Model 47 and 54	Protocol, age, gender, time, BMI, VO_2max
Model 48 and 55	Protocol, age, gender, BMI, time, HR
Model 49 and 56	Protocol, age, gender, BMI, time, VO2max, HR

Table 4.2. Overview of VO_2max models along with their predictor variables.

Models	**Predictor Variables**
Model 57	Age, gender, height, weight, HR
Model 58	Age, gender, height, weight, time
Model 59	Age, gender, height, weight, HRLT
Model 60	Age, gender, height, weight, time, HR
Model 61	Age, gender, height, weight, HR, HRLT
Model 62	Age, gender, height, weight, time, HRLT
Model 63	Age, gender, height, weight,time, HR, HRLT
Model 64	Age, gender, BMI, HR
Model 65	Age, gender, BMI, time
Model 66	Age, gender, BMI, HRLT
Model 67	Age, gender, BMI, time, HR
Model 68	Age, gender, BMI, HR, HRLT
Model 69	Age, gender, BMI, time, HRLT
Model 70	Age, gender, BMI, time, HR, HRLT
Model 71	Protocol, age, gender, height, weight, HR
Model 72	Protocol, age, gender, height, weight, time
Model 73	Protocol, age, gender, height, weight, HRLT
Model 74	Protocol, age, gender, height, weight, time, HR
Model 75	Protocol, age, gender, height, weight, HR, HRLT
Model 76	Protocol, age, gender, height, weight, time, HRLT
Model 77	Protocol, age, gender, height, weight,time, HR, HRLT
Model 78	Protocol, age, gender, BMI, HR
Model 79	Protocol, age, gender, BMI, time
Model 80	Protocol, age, gender, BMI, HRLT
Model 81	Protocol, age, gender, BMI, time, HR
Model 82	Protocol, age, gender, BMI, HR, HRLT
Model 83	Protocol, age, gender, BMI, time, HRLT
Model 84	Protocol, age, gender, BMI, time, HR, HRLT

4.1. SVM model for predicting UBP and VO_2max

The type of kernel function, kernel function parameters, the value of C, and the value of ε for the ε-insensitive loss function are the major components that affect the quality and performance of a SVM model. Parameter C determines the tradeoff cost between minimizing the training error and minimizing model complexity. A small value for C will increase the number of training errors, while a large C will lead to a behavior similar to that of a hard-margin SVM. Parameter ε controls the width of ε-insensitive zone. In addition, ε determines the number of support vectors; smaller values of ε may lead to more support vectors and result in a complex learning machine and vice versa. The kernel parameters define the nonlinear mapping from the input space to high-dimensional feature space (Ji & Wang, 2007). We chose to use the RBF kernel defined as $\exp\left\{-\gamma\left|\mathbf{x}_i-\mathbf{x}_j\right|^2\right\}$ for developing our SVM model. The parameter that should be optimized for the RBF kernel is the function parameter γ.

It is not known beforehand which C, ε and γ are the best for a given regression problem, therefore some sort of parameter search must be conducted. The purpose is to find optimized values of the triple (C, ε, γ) so that the regression model can predict testing data with minimum error. Many methods for selecting the optimal parameters have been proposed, for example, cross validation, grid search (Hsu, 2003), particle swarm optimization (Guo, 2006), genetic algorithm (Friedrichs, 2005), etc. For median-sized problems, the grid search method is an efficient method for finding the optimum values of C, ε and γ. In grid search, the parameters are varied by fixed step-sizes through a range of values, and the performance of each set of parameters is measured and compared. When performing a search for optimal parameters, different criteria such as maximizing correlation coefficient, minimizing root mean squared error or mean absolute error can be used for determining the optimum function value. To improve the generalization ability, grid search can use a cross validation process. In k-fold cross validation, the original dataset is partitioned into k subsets. Of the k subsets, a single subset is retained as the validation data for

testing the model, and the remaining $k-1$ subsets are used as training data. The cross validation process is then repeated k times (the *folds*), with each of the k subsets used exactly once as the validation data. The k results from the folds then can be averaged (or combined) to produce a single estimation.

In this study, we use grid search together with 5-fold cross validation to determine the best values of C, ε and γ. To guarantee that the prediction models developed by using SVM are valid and can be generalized for making new predictions regarding new data, the dataset is partitioned into training and independent test sets via a 10-fold cross validation. Figure 4.1 shows the flow chart of our SVM-based model for predicting UBP and VO_2max for a single fold. Initially, the train and test subsets are standardized to have zero mean and unit variance, so new train and test subsets are created. This process avoided predictor variables in greater numeric ranges dominate those in smaller numeric ranges and the computational difficulty associated with using larger numeric values. For each value of (C, ε, γ) triple, 5-fold cross validation is conducted on the new training subset and root mean squared errors of each prediction are calculated. The (C, ε, γ) triple that yields the lowest overall root mean squared error is chosen for training the train subset. The prediction model is developed after training subset is trained with the optimized values of C, ε and γ. Lastly, the prediction model is used to estimate UBP and VO_2max values in the new test subset.

4.2. MLP model for predicting UBP and VO_2max

Back-propagation MLP is used to develop models for prediction of UBP and VO_2max. The performance of an MLP depends on the number of hidden layers and the number of neurons in each hidden layer. The less neuron used, the less information will be obtained; in contrast, the local minimum may increase, and the network may converge to a local minimum mostly. Thus the network's precision will fall. However, there is not a rule in defining the number of neurons in a hidden layer. In general, the optimal number is empirically chosen based on the physical complexity of the problem.

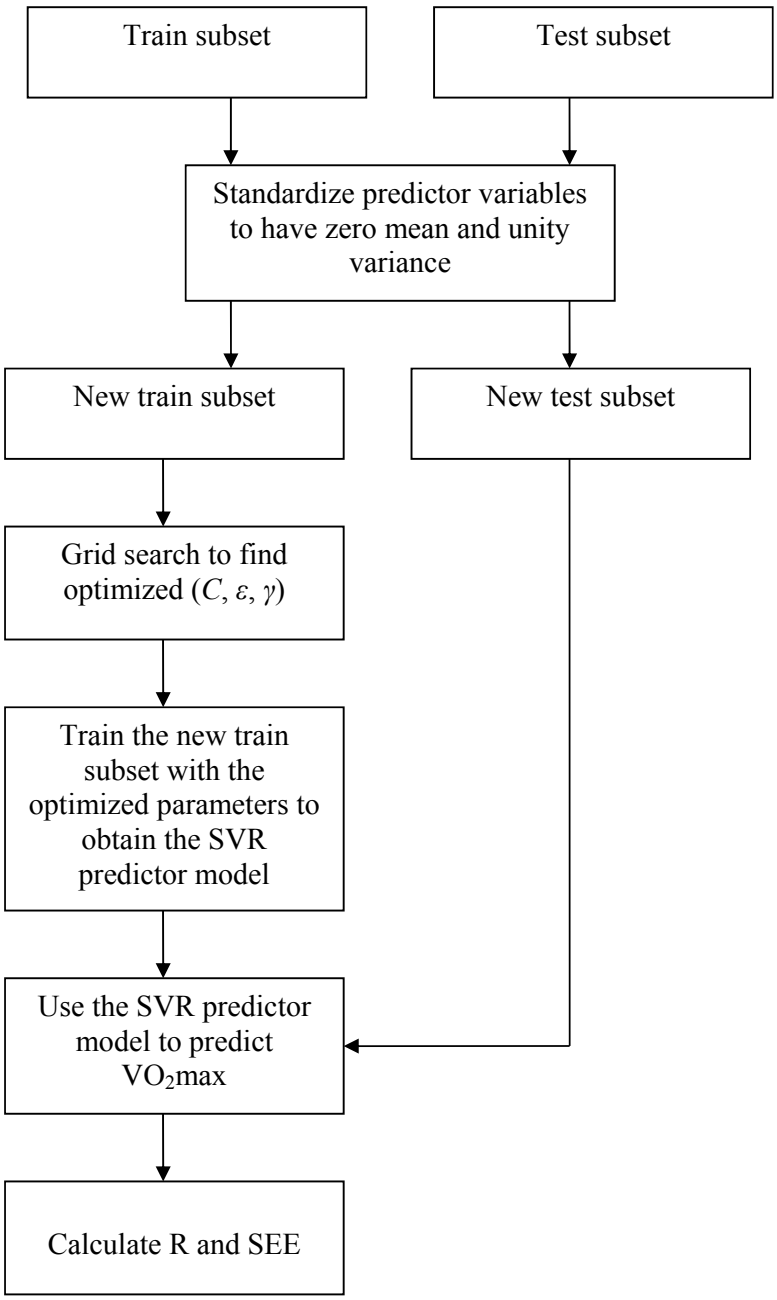


Figure 4.1. Flow chart of the SVM-based model for predicting UBP and VO_2max for a single fold

The inputs and outputs are normalized so that they have zero mean and unity variance. Also, the inputs have been pre-processed by using the Principal Component Analysis (PCA) method to orthogonalize the components of the input vectors (so that they are uncorrelated with each other) and to order the resulting orthogonal components (principal components) so that those with the largest variation come first (Jackson, 2001). The tansigmoid activation function is used in the hidden layers, the pure-linear activation function is used in the hidden layers, and the Levenberg-Marquardt algorithm is utilized for training the network. The other important parameters of the MLP models are the number of epochs (selected as 100), the learning rate and momentum.

Table 4.3. *R* and *SEE* values for UBP_{10} prediction models using different regression methods on the UBP-set1 data set.

Models	**MLR**		**SVM-Linear**		**MLP**		**SVM-RBF**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 1	0.86	38.47	0.89	33.94	0.90	32.06	0.91	31.66
Model 2	0.85	38.63	0.89	36.27	0.89	33.32	0.90	32.42
Model 3	0.86	38.86	0.89	37.99	0.88	34.24	0.89	33.68
Model 4	0.85	39.55	0.89	38.38	0.86	37.67	0.89	35.19
Model 5	0.81	45.16	0.90	43.54	0.86	38.45	0.91	36.07
Model 6	0.80	50.13	0.77	46.96	0.83	43.03	0.89	36.08
Model 7	0.75	52.82	0.76	50.65	0.81	46.32	0.89	37.93

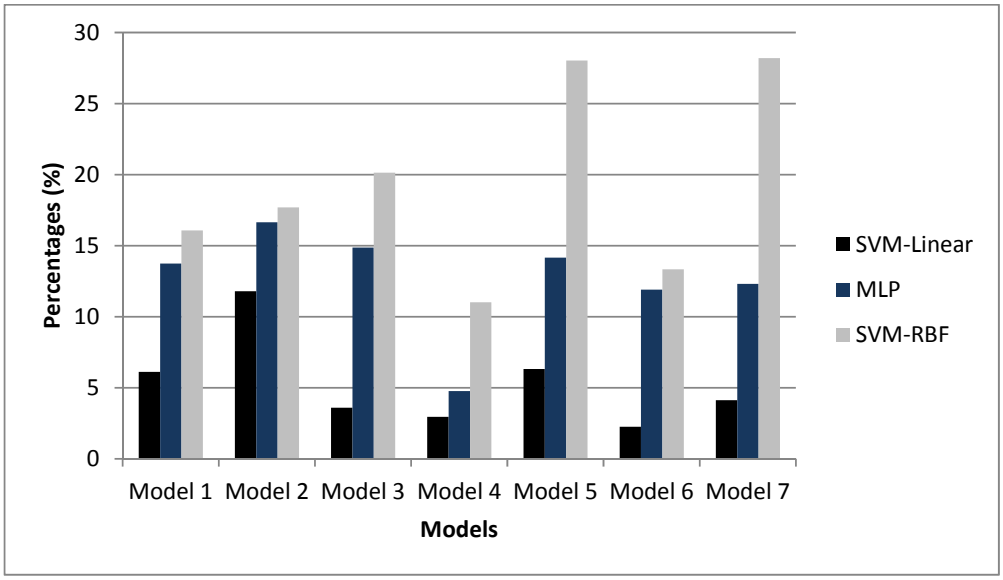


Figure 4.2. Percentage decrease rates in *SEE*'s of UBP_{10} for machine learning methods compared to *SEE*'s obtained by MLR (UBP-set1)

Table 4.4. *R* and *SEE* values for UBP_{60} prediction models using different regression methods on the UBP-set1 data set.

Models	**MLR**		**SVM-Linear**		**MLP**		**SVM-RBF**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 8	0.93	19.63	0.94	19.05	0.94	18.97	0.95	18.11
Model 9	0.93	20.43	0.93	20.32	0.94	20.25	0.94	19.55
Model 10	0.91	24.46	0.92	23.21	0.93	20.81	0.93	20.02
Model 11	0.91	24.46	0.92	23.63	0.93	20.94	0.93	20.04
Model 12	0.90	25.09	0.91	24.15	0.92	21.27	0.93	20.69
Model 13	0.89	26.51	0.91	24.74	0.92	23.27	0.92	21.48
Model 14	0.87	29.79	0.90	27.65	0.90	24.34	0.92	22.60

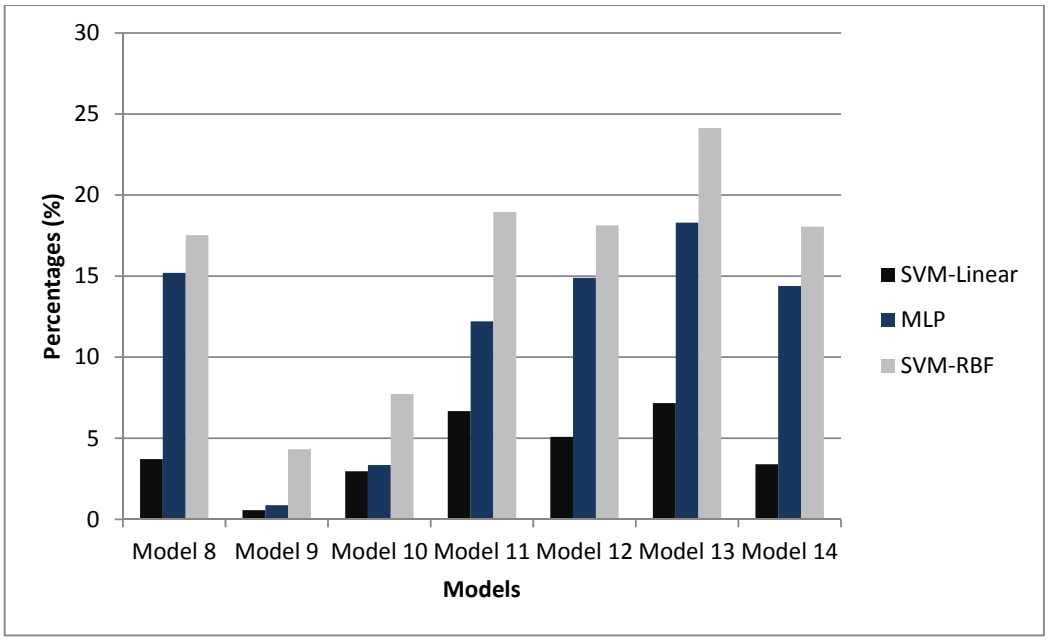


Figure 4.3. Percentage decrease rates in *SEE*'s of $UBP_{60}$for machine learning methods compared to *SEE*'s obtained by MLR (UBP-set1)

Table 4.5. *R* and *SEE* values for UBP_{10} prediction models using different regression methods on the UBP-set2 data set.

Models	**MLR**		**SVM-Linear**		**MLP**		**SVM-RBF**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 15	0.81	41.17	0.82	40.00	0.84	39.97	0.85	38.91
Model 16	0.81	42.55	0.81	41.60	0.82	40.13	0.84	39.35
Model 17	0.79	44.10	0.80	43.37	0.82	42.91	0.82	40.20
Model 18	0.76	47.92	0.79	45.78	0.80	44.61	0.82	40.66
Model 19	0.75	48.35	0.76	47.60	0.79	46.50	0.81	42.34
Model 20	0.68	53.42	0.75	49.18	0.78	48.99	0.79	47.59
Model 21	0.67	57.97	0.64	51.91	0.71	50.96	0.73	49.11

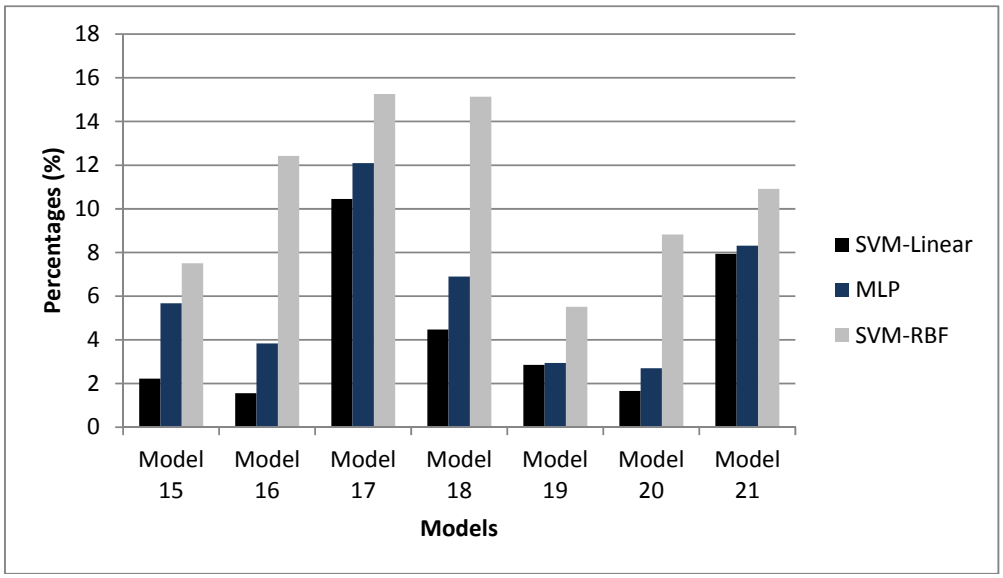


Figure 4.4. Percentage decrease rates in *SEE*'s of UBP_{10} for machine learning methods compared to *SEE*'s obtained by MLR (UBP-set2)

Table 4.6. *R* and *SEE* values for UBP_{60} prediction models using different regression methods on the UBP-set2 data set.

Models	**MLR**		**SVM-Linear**		**MLP**		**SVM-RBF**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 22	0.89	25.18	0.89	24.97	0.90	24.29	0.90	23.84
Model 23	0.88	27.63	0.89	26.61	0.87	25.19	0.91	24.59
Model 24	0.88	28.71	0.88	27.46	0.88	26.40	0.90	25.30
Model 25	0.87	28.99	0.87	27.81	0.88	27.11	0.90	26.03
Model 26	0.83	31.17	0.84	30.06	0.85	29.21	0.85	28.70
Model 27	0.84	31.98	0.88	30.22	0.85	29.87	0.89	29.33
Model 28	0.70	39.38	0.73	38.47	0.52	38.11	0.74	37.60

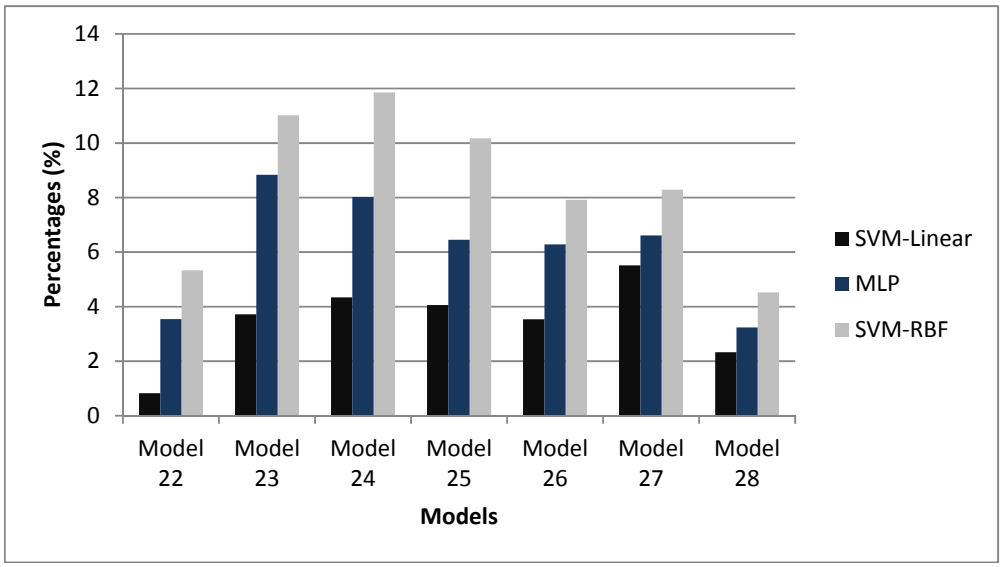


Figure 4.5. Percentage decrease rates in *SEE*'s of UBP_{60} for machine learning methods compared to *SEE*'s obtained by MLR (UBP-set2)

Table 4.7. *R* and *SEE* values for UBP_{10} prediction models using different regression methods on the UBP-set3 data set.

Models	**MLR**		**SVM-Linear**		**MLP**		**SVM-RBF**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 29	0.86	39.40	0.90	34.12	0.89	33.75	0.91	32.21
Model 30	0.85	39.87	0.89	38.59	0.88	37.83	0.91	33.47
Model 31	0.84	41.75	0.88	39.43	0.88	38.27	0.90	34.02
Model 32	0.83	46.14	0.87	44.57	0.87	39.69	0.89	36.20
Model 33	0.83	46.81	0.86	45.52	0.85	41.55	0.89	37.93
Model 34	0.77	51.26	0.86	51.73	0.83	44.37	0.88	39.62
Model 35	0.76	53.59	0.84	52.94	0.81	48.99	0.87	43.25

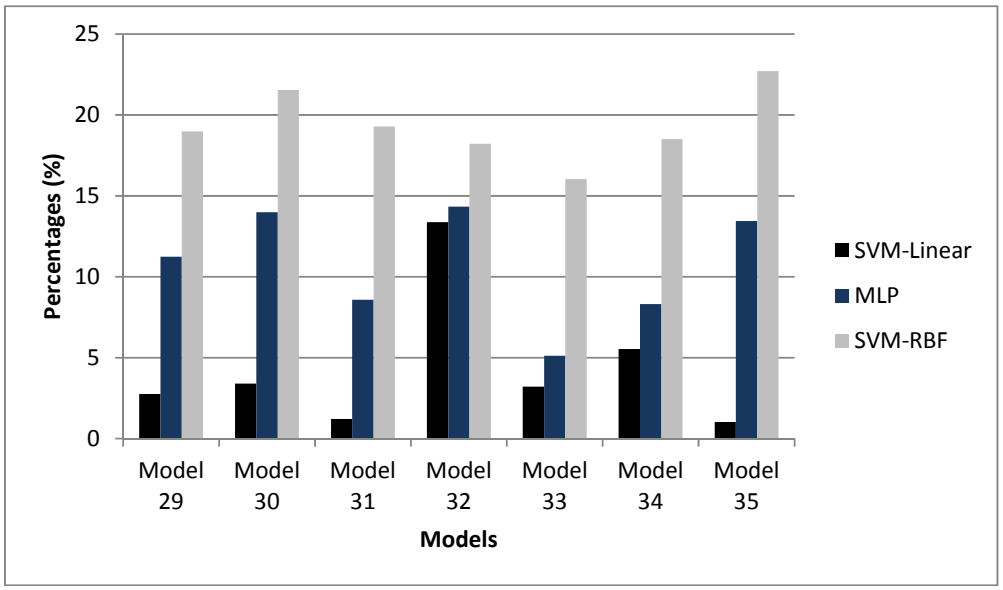


Figure 4.6. Percentage decrease rates in *SEE*'s of UBP_{10} for machine learning methods compared to *SEE*'s obtained by MLR (UBP-set3)

Table 4.8. *R* and *SEE* values for UBP_{60} prediction models using different regression methods on the UBP-set3 data set.

Models	**MLR**		**SVM-Linear**		**MLP**		**SVM-RBF**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 36	0.89	25.87	0.92	24.44	0.91	23.65	0.93	20.37
Model 37	0.89	27.84	0.91	24.73	0.91	24.11	0.93	21.46
Model 38	0.88	28.47	0.91	25.00	0.90	24.97	0.93	21.55
Model 39	0.87	28.61	0.90	25.89	0.89	25.55	0.92	24.57
Model 40	0.85	29.99	0.89	26.77	0.89	25.58	0.91	25.17
Model 41	0.84	34.25	0.89	32.37	0.89	29.52	0.90	26.65
Model 42	0.79	36.80	0.81	34.52	0.85	30.76	0.90	27.21

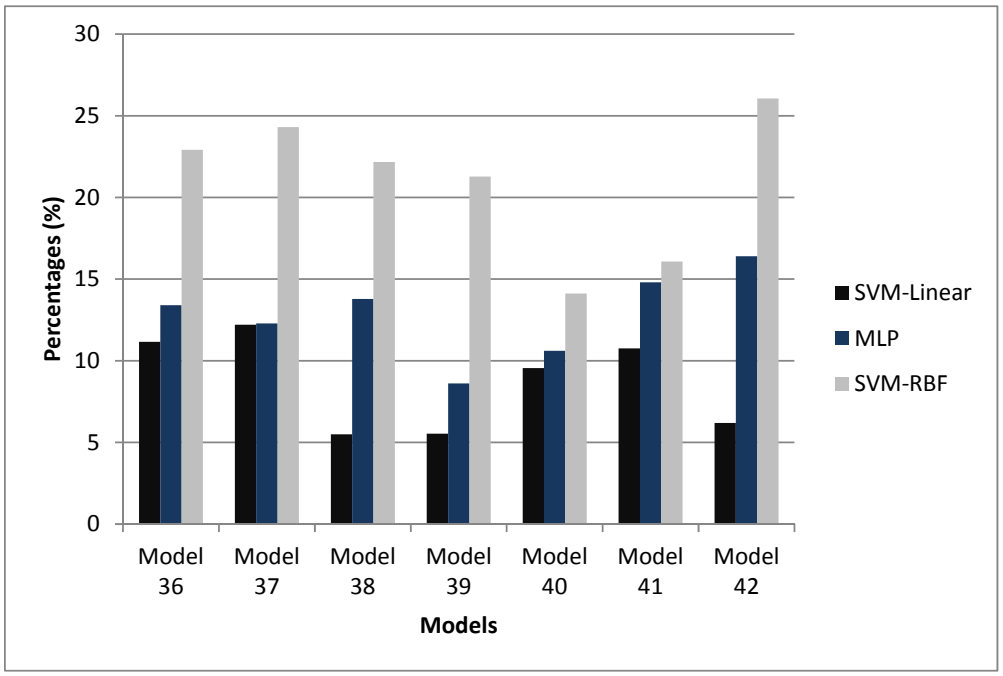


Figure 4.7. Percentage decrease rates in *SEE*'s of UBP_{60} for machine learning methods compared to *SEE*'s obtained by MLR (UBP-set3)

Table 4.9. *R* and *SEE* values for UBP_{10} prediction models using different regression methods on the UBP-set4 data set.

Models	**MLR**		**SVM-Linear**		**MLP**		**SVM-RBF**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 43	0.83	41.94	0.84	40.78	0.84	40.59	0.87	39.31
Model 44	0.80	44.86	0.83	43.83	0.83	42.86	0.85	41.06
Model 45	0.79	49.98	0.82	47.31	0.82	45.02	0.84	42.99
Model 46	0.79	51.29	0.82	48.51	0.80	47.33	0.84	43.62
Model 47	0.76	51.60	0.80	50.98	0.80	48.15	0.83	45.61
Model 48	0.72	60.32	0.80	52.91	0.80	50.60	0.81	49.38
Model 49	0.63	62.86	0.69	53.00	0.71	52.06	0.70	47.30

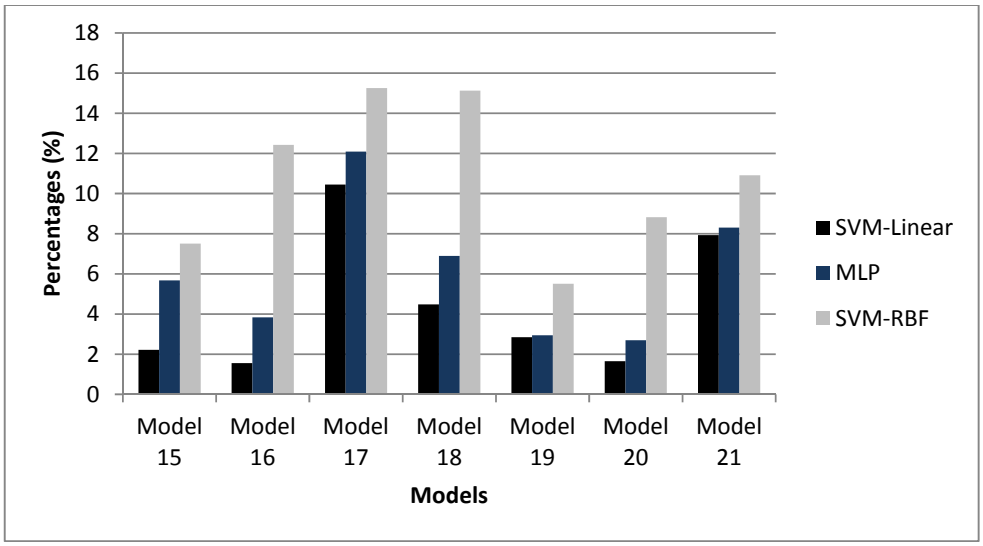


Figure 4.8. Percentage decrease rates in *SEE*'s of UBP_{10} for machine learning methods compared to *SEE*'s obtained by MLR (UBP-set4)

Table 4.10. *R* and *SEE* values for UBP_{60} prediction models using different regression methods on the UBP-set4 data set.

Models	**MLR**		**SVM-Linear**		**MLP**		**SVM-RBF**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 50	0.88	28.25	0.88	27.53	0.89	25.85	0.89	24.88
Model 51	0.88	28.41	0.88	28.17	0.88	27.72	0.89	27.50
Model 52	0.86	29.16	0.88	29.02	0.88	28.51	0.89	27.72
Model 53	0.85	29.20	0.87	29.05	0.85	28.72	0.89	28.03
Model 54	0.83	31.59	0.86	30.34	0.85	29.91	0.86	29.23
Model 55	0.82	35.67	0.85	33.11	0.84	32.61	0.85	30.93
Model 56	0.67	44.63	0.70	40.15	0.72	38.62	0.75	38.13

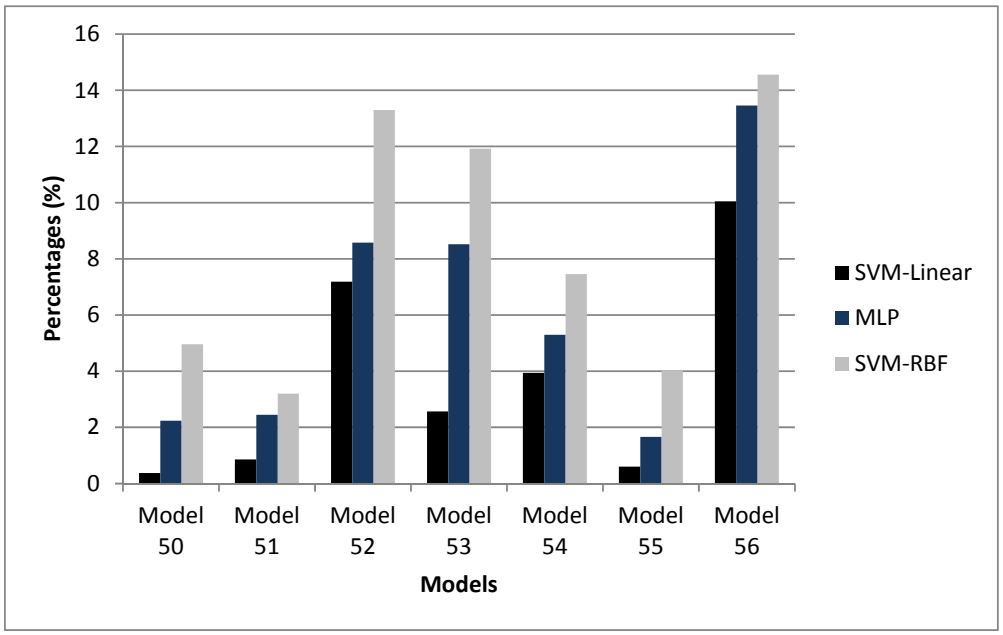


Figure 4.9. Percentage decrease rates in *SEE*'s of UBP_{60} for machine learning methods compared to *SEE*'s obtained by MLR (UBP-set4)

Table 4.11. *R* and *SEE* values for VO_2max prediction models using different regression methods on the VO_2 max-set1 data set.

Models	**MLR**		**SVM-Linear**		**MLP**		**SVM-RBF**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 57	0.88	3.75	0.88	3.71	0.89	3.70	0.89	3.69
Model 58	0.88	3.76	0.88	3.73	0.88	3.72	0.88	3.71
Model 59	0.86	4.17	0.87	4.14	0.87	3.90	0.88	3.81
Model 60	0.85	4.29	0.87	4.21	0.87	4.04	0.88	3.82
Model 61	0.83	4.39	0.83	4.36	0.84	4.35	0.84	4.29
Model 62	0.83	4.40	0.84	4.36	0.84	4.36	0.84	4.36
Model 63	0.80	4.60	0.81	4.59	0.81	4.58	0.82	4.54

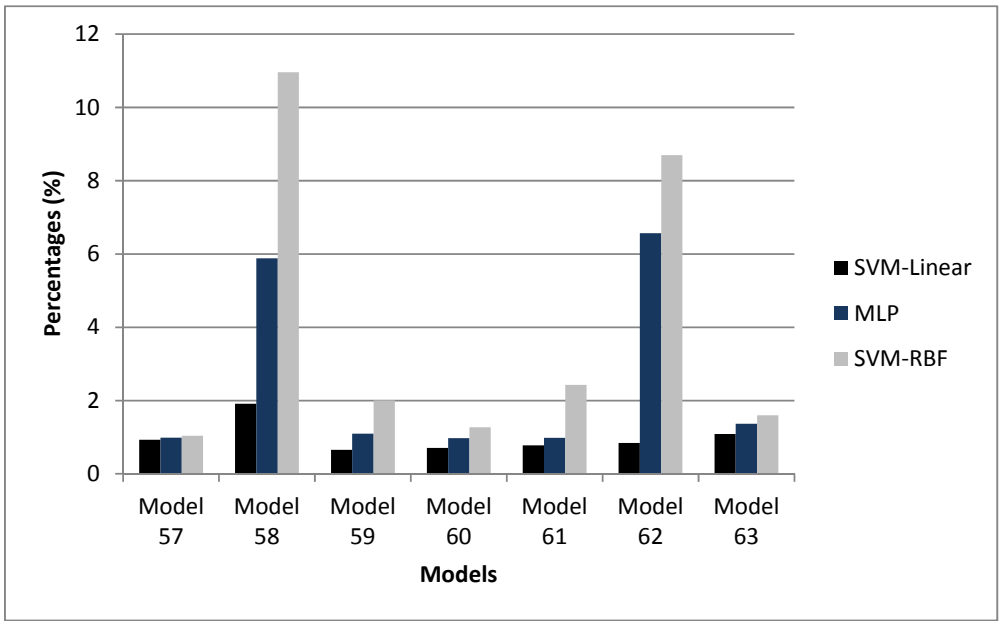


Figure 4.10. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR (VO_2max-set1)

Table 4.12. *R* and *SEE* values for VO_2max prediction models using different regression methods on the VO_2 max-set2 data set.

Models	**MLR**		**SVM-Linear**		**MLP**		**SVM-RBF**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 64	0.84	4.35	0.85	4.18	0.86	4.15	0.87	4.01
Model 65	0.84	4.43	0.85	4.20	0.86	4.16	0.87	4.05
Model 66	0.83	4.45	0.85	4.45	0.84	4.43	0.86	4.31
Model 67	0.83	4.47	0.83	4.45	0.83	4.44	0.86	4.33
Model 68	0.81	4.74	0.83	4.61	0.83	4.49	0.86	4.36
Model 69	0.81	4.76	0.81	4.66	0.83	4.53	0.84	4.46
Model 70	0.77	5.16	0.81	4.76	0.83	4.71	0.81	4.63

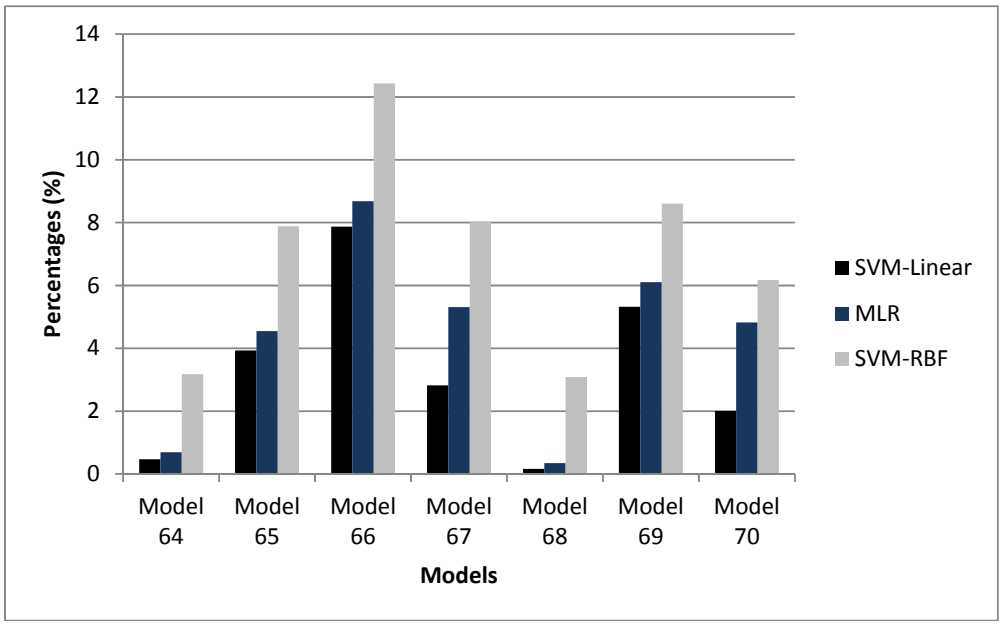


Figure 4.11. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR (VO_2max-set2)

Table 4.13. *R* and *SEE* values for VO_2max prediction models using different regression methods on the VO_2 max-set3 data set.

Models	**MLR**		**SVM-Linear**		**MLP**		**SVM-RBF**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 71	0.83	4.42	0.82	4.40	0.83	4.39	0.83	4.38
Model 72	0.83	4.43	0.83	4.41	0.83	4.40	0.83	4.38
Model 73	0.83	4.44	0.83	4.43	0.82	4.43	0.83	4.40
Model 74	0.82	4.46	0.83	4.44	0.83	4.44	0.83	4.41
Model 75	0.80	4.68	0.81	4.64	0.81	4.62	0.82	4.49
Model 76	0.80	4.70	0.81	4.67	0.81	4.66	0.81	4.64
Model 77	0.76	5.23	0.79	5.03	0.78	5.00	0.80	4.79

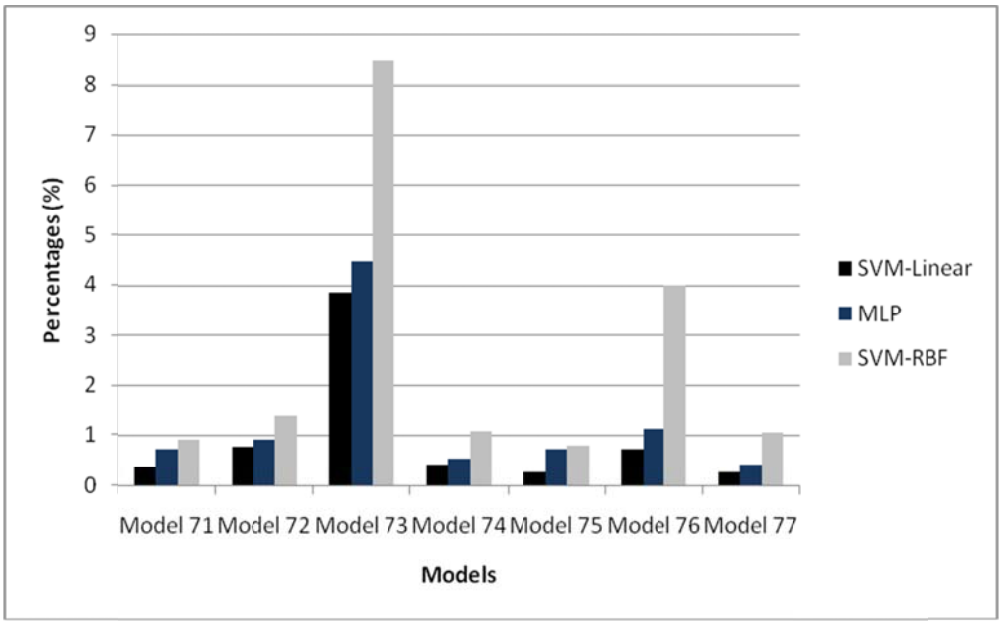


Figure 4.12. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR (VO_2max-set3)

Table 4.14. *R* and *SEE* values for VO_2max prediction models using different regression methods on the VO_2 max-set4 data set.

Models	**MLR**		**SVM-Linear**		**MLP**		**SVM-RBF**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 78	0.80	4.73	0.81	4.68	0.81	4.64	0.83	4.39
Model 79	0.80	4.82	0.80	4.73	0.81	4.67	0.83	4.39
Model 80	0.79	4.98	0.81	4.97	0.80	4.77	0.83	4.40
Model 81	0.78	4.99	0.81	4.97	0.80	4.82	0.82	4.47
Model 82	0.77	5.22	0.80	5.07	0.79	4.93	0.82	4.58
Model 83	0.76	5.22	0.79	5.19	0.79	4.97	0.82	4.68
Model 84	0.75	5.23	0.75	5.20	0.77	5.10	0.81	4.81

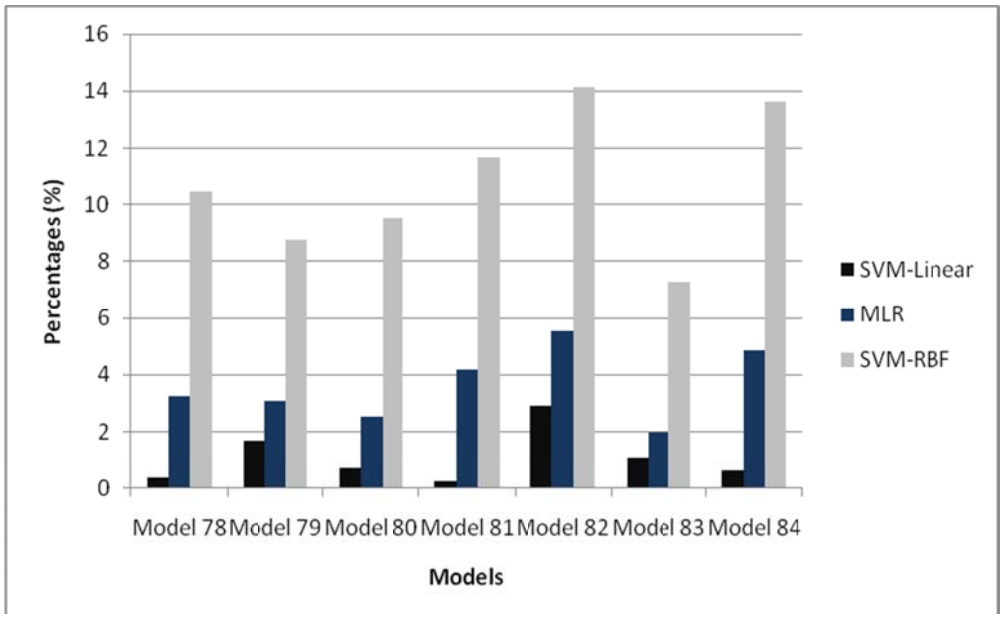


Figure 4.13. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR (VO_2max-set4)

4.3. Discussions on UBP_{10} Results

- The results from Table 4.3, Table 4.5, Table 4.7, and Table 4.9 show that SVM-RBF-based UBP_{10} prediction models perform better than MLP-based, SVM-Linear-based, and MLR-based prediction models. MLP-based UBP_{10} prediction models are more accurate than SVM-Linear-based and MLR-based prediction models, and SVM-Linear-based UBP_{10} prediction models have better *SEE* values than MLR-based prediction models.
- Among the SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, Model 1, which includes age, gender, weight, height, and VO_2max, has the lowest *SEE*'s (31.66, 32.06, 33.94, and 38.47, respectively) and the highest *R*'s (0.91, 0.90, 0.89, and 0.86, respectively).
- Among the SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, Model 7, which includes age, gender, weight, height, HR, VO_2max, and time has the highest *SEE*'s (37.93, 46.32, 50.65, and 52.82, respectively) and the lowest *R*'s (0.89, 0.81, 0.76, and 0.75, respectively) The inclusion of RVO_2max and exercise time in prediction models of UBP_{10} (Table 4.3) yields 19.78%, 44.46%, 49.26%, and 37.32% augmentations in *SEE'*s for the SVM-RBF-b*ase*d, MLP-based, SVM-Linear-based, and MLR-based models, respectively.
- When Table 4.3 is compared with Table 4.7, it can easily be seen that inclusion of the "protocol" variable yields increments in *SEE*'s for all UBP prediction models.
- It can be seen from Table 4.7 that Model 29 with the predictor variables, protocol, age, gender, weight, height, and VO_2max gives the lowest *SEE*'s (32.21, 33.75, 34.12, and 39.40) and the highest *R*'s (0.91, 0.89, 0.90, and 0.86) for the SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, respectively.
- Inclusion of time and HR variables to the best model of UBP_{10} (Table 4.5) yields 23.00%, 31.49%, 48.69%, and 30.14% increments in *SEE*'s and

2.76%, 8.68%, 4.77%, and 9.04% decrements in *R*'s for SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, respectively.

- By adding BMI to all models and removing the variables height and weight from all prediction models in Table 4.3, which is shown in Table 4.5, we obtain higher *SEE*'s Model 15, the best prediction model of Table 4.5, includes the attributes age, gender, BMI, and VO_2max.
- Reductions in *SEE*'s between the best model of Table 4.3 and Table 4.5 are 18.61%, 19.76%, 15.16%, and 6.57% for SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, respectively.
- Similarly, inclusion of BMI to all prediction models and extraction of weight and height from all prediction models in Table 4.7, which is given in the Table 4.9, we comparatively obtain worse *SEE*'s Decrements in *SEE*'s between the best prediction models of Table 4.7 and Table 4.9 are 18.05%, 16.85%, 16.33%, and 4.94% for SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, in the order given.
- When we cover Table 4.3, Table 4.5, Table 4.7, and Table 4.9 for UBP_{10} prediction models, we get the lowest *SEE*'s in Model 1 with SVM-RBF method.

4.4. Discussions on UBP_{60} Results

- The outcomes from Table 4.4, Table 4.6, Table 4.8, and Table 4.10 indicate that SVM-RBF-based UBP_{60} prediction models comparatively give better *SEE*'s than MLP-based, SVM-Linear-based, and MLR-based prediction models. MLP-based UBP_{60} prediction models perform better than SVM-Linear-based and MLR-based prediction models, and SVM-Linear-based UBP_{60} prediction models give more accurate *SEE*'s than MLR-based prediction models.
- From Table 4.4, it can be seen that Model 8, which has the attributes age, gender, weight, height, and VO_2max has the lowest *SEE*'s (18.11, 18.97, 19.05, and 19.63) and highest *R*'s (0.95, 0.94, 0.94, and 0.93) for the SVM-

RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, respectively.

- Among the SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, Model 14, which includes age, gender, weight, height, VO_2max, time and HR has the highest *SEE*'s (22.60, 24.34, 27.65, and 29.79) and the lowest *R*'s (0.92, 0.90, 0.90, and 0.87), in the order given.
- From Table 4.8, it is clearly seen that Model 36 with the variables, protocol, age, gender, weight, height, and VO_2max, has the best *SEE*'s values (20.37, 23.65, 24.44, and 25.87) whereas Model 42 with the attributes protocol, age, gender, weight, height, time, VO_2max, time, and HR has the highest *SEE*'s (27.21, 30.76, 34.52, and 36.80) and the lowest *R*'s (0.90, 0.85, 0.81, and 0.79) for the SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, in the order given.
- By including HR and time to the best prediction model of Table 4.8, 33.60%, 30.10%, 41.23%, and 42.23% increments in *SEE*'s and 2.78%, 6.24%, 10.88%, and 11.36% decrements in *R*'s for the SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, respectively have been obtained.
- Inclusion of BMI to all prediction models and extraction of weight and height from all prediction models (Table 4.6 and Table 4.8) yields, higher *SEE*'s and lower *R*'s.
- Decreasing in *SEE*'s between the best prediction models of Table 4.6 and Table 4.8 are 18.15%, 8.51%, 11.22%, and 8.42% for the SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, respectively.
- In a similar manner, we obtain Table 4.10 by adding BMI to Table 4.8 and removing weight and height from the Table 4.8. It is clearly seen that this process increases the *SEE*'s to 24.88, 25.85, 27.53, 28.25 for the SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, respectively which is model 50 that includes protocol, age, gender, BMI, and VO_2max.

4.5. Discussion between the Results of UBP_{10} and UBP_{60}

- It is clear from Table 4.3, Table 4.5, Table 4.7, and Table 4.9 that prediction models including protocol (Table 4.3 and Table 4.5 does not include this variable) age, gender, weight, height, and VO_2max has the best value of *SEE*'s, and similarly, it is easily seen from Table 4.5, Table 4.6, Table 4.9, and Table 4.10 that prediction models including protocol (Table 4.5 and Table 4.6 does not include this variable), age, gender, BMI, and RVO_2max give the lowest *SEE*'s scores.
- From all the tables we obtained, it can be seen that using all attributes yield the worst *SEE* scores.
- The results from 4.3, Table 4.4, Table 4.5, Table 4.6, Table 4.7, Table 4.8, Table 4.9, and Table 4.10 show that UBP_{60} has lower *SEE* scores than UBP_{10}'s which means prediction of UBP_{60} is more accurate.

4.6. Discussion on VO_2max Results

- The results obtained from the Table 4.11, Table 4.12, Table 4.13 and Table 4.14 represent that SVM-RBF-based VO_2max prediction models have lower *SEE*'s than MLP-based, SVM-Linear-based, and MLR-based prediction models. MLP-based VO_2max prediction models comparatively give more accurate results than SVM-Linear-based and MLR-based prediction models, and SVM-Linear-based VO_2max prediction models perform better than MLR-based prediction models.
- From Table 4.11, it can be seen that Model 57 with the attributes, age, gender, weight, height, and HR has the lowest *SEE*'s (3.69, 3.70, 3.71, and 3.75) and highest *R*'s (0.89, 0.89, 0.88, and 0.88), whereas Model 63, which includes age, gender, weight, height, time, HR and HRLT has the highest *SEE*'s (4.54, 4.58, 4.59, and 4.60) and the lowest *R*'s (0.82, 0.81, 0.81, and 0.80) for the SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, in the order given.

- Among the SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, it is clear from Table 4.13 that Model 71 including the predictor variables protocol, age, gender, weight, height and HR gives the lowest *SEE*'s (4.38, 4.39, 4.40, and 4.42), while Model 77 with protocol, age, gender, weight, height, time, HR and HRLT attributes has the highest *SEE*'s (4.79, 5.00, 5.03, and 5.23), respectively.
- Inclusion of BMI to all prediction models and extraction of weight and height from all prediction models (Table 4.11 and Table 4.12), yields higher SEE's and lower R's for SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models. We get the models given in Table 4.14 by adding the BMI attribute to the models given in Table 4.13 and removing the weight and height attributes from Table 4.13. It is clearly seen that the *SEE* scores in Table 4.14 increase to 4.39, 4.64, 4.68 and 4.73 for the SVM-RBF-based, MLP-based, SVM-Linear-based, and MLR-based models, respectively for Model 78 that includes protocol, age, gender, BMI, and HR.

Finally, below are given the scatter plots of actual vs. predicted UBP scores as well as VO_2max scores for each best model from the eight data sets using SVM-RBF.

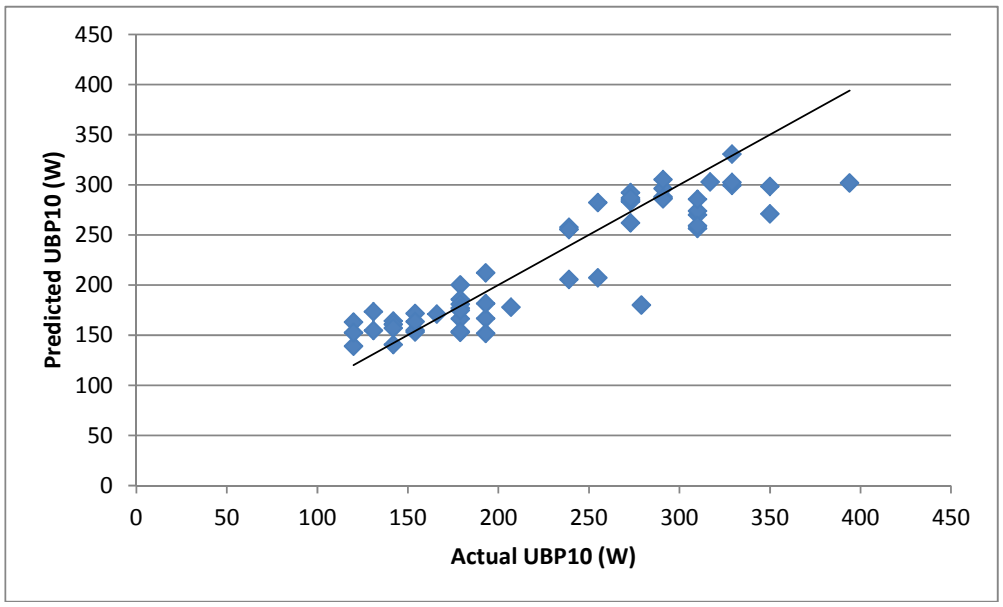


Figure 4.14. Scatter plot of actual UBP_{10} vs. predicted UBP_{10} for Model 1 using SVM-RBF

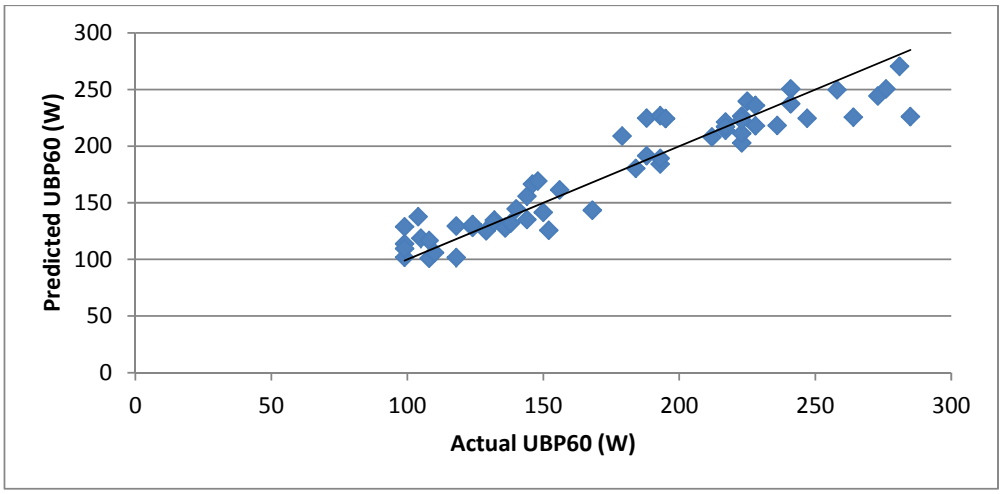


Figure 4.15. Scatter plot of actual UBP_{60} vs. predicted UBP_{60} for Model 8 using SVM-RBF

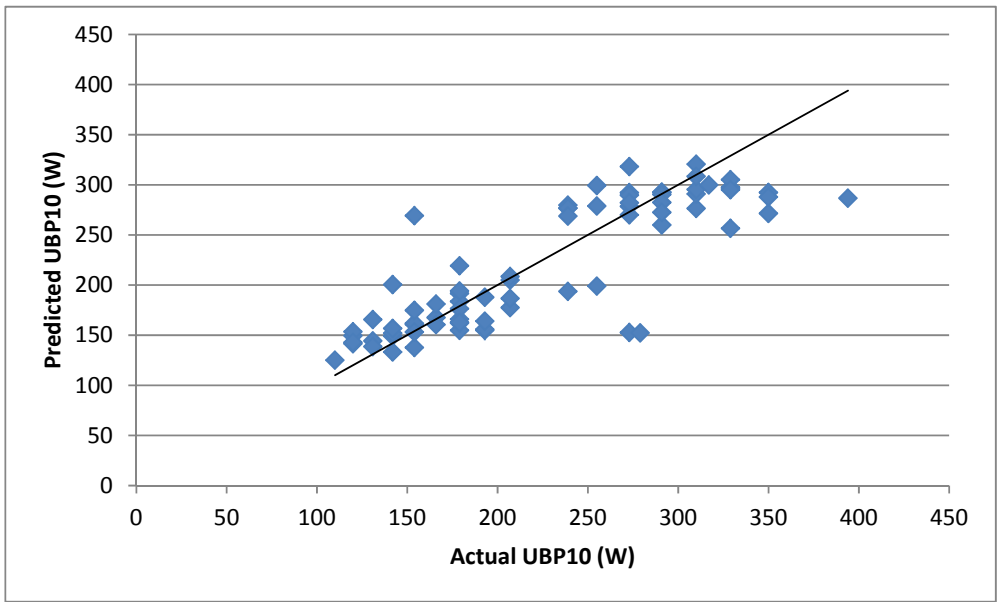


Figure 4.16. Scatter plot of actual UBP_{10} vs. predicted UBP_{10} for Model 15 using SVM-RBF

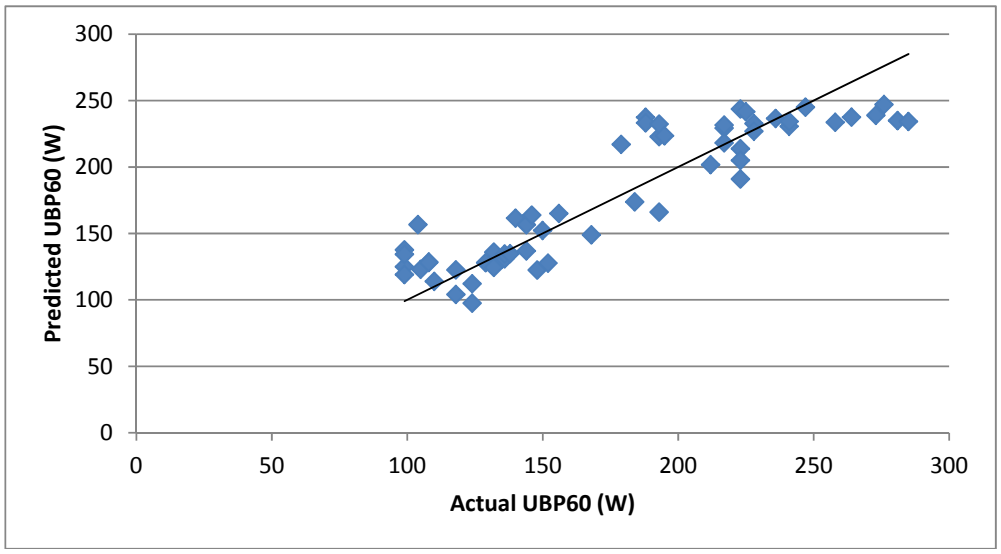


Figure 4.17. Scatter plot of actual UBP_{60} vs. predicted UBP_{60} for Model 22 using SVM-RBF

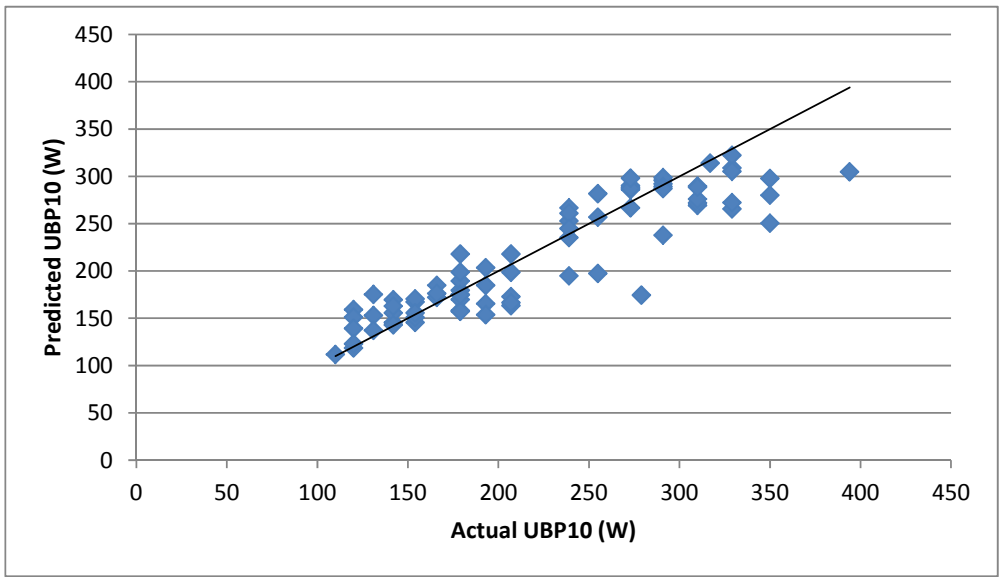


Figure 4.18. Scatter plot of actual UBP_{10} vs. predicted UBP_{10} for Model 29 using SVM-RBF

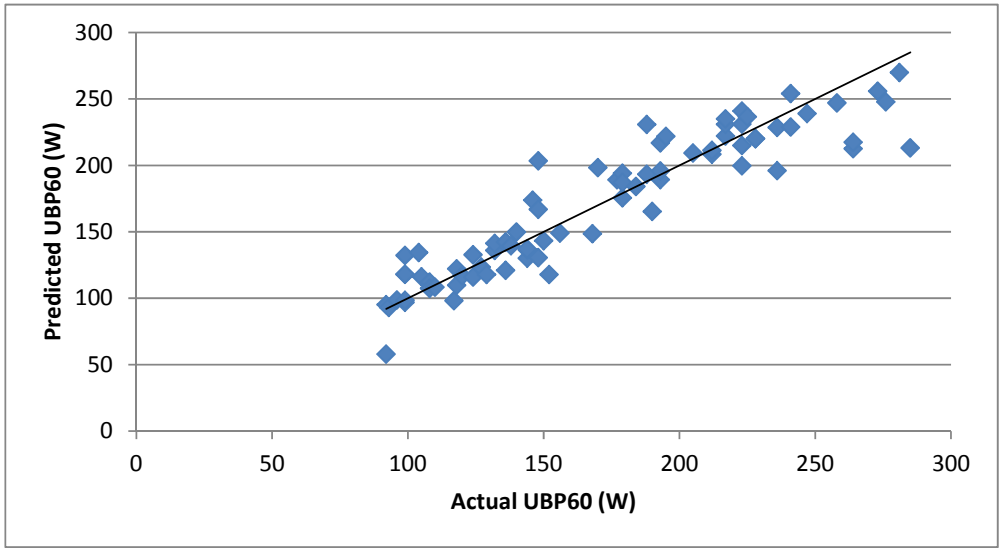


Figure 4.19. Scatter plot of actual UBP_{60} vs. predicted UBP_{60} for Model 36 using SVM-RBF

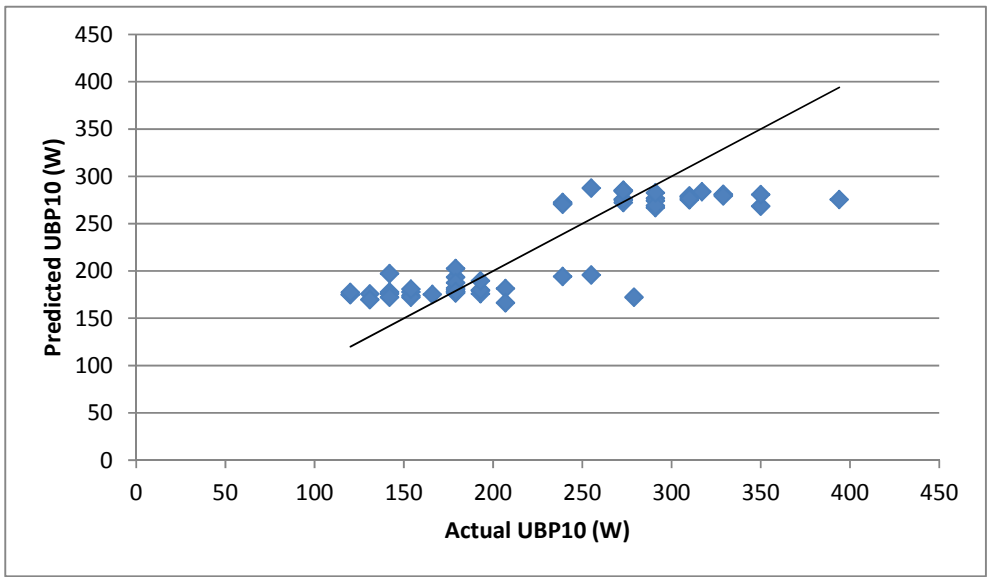


Figure 4.20. Scatter plot of actual UBP_{10} vs. predicted UBP_{10} for Model 43 using SVM-RBF

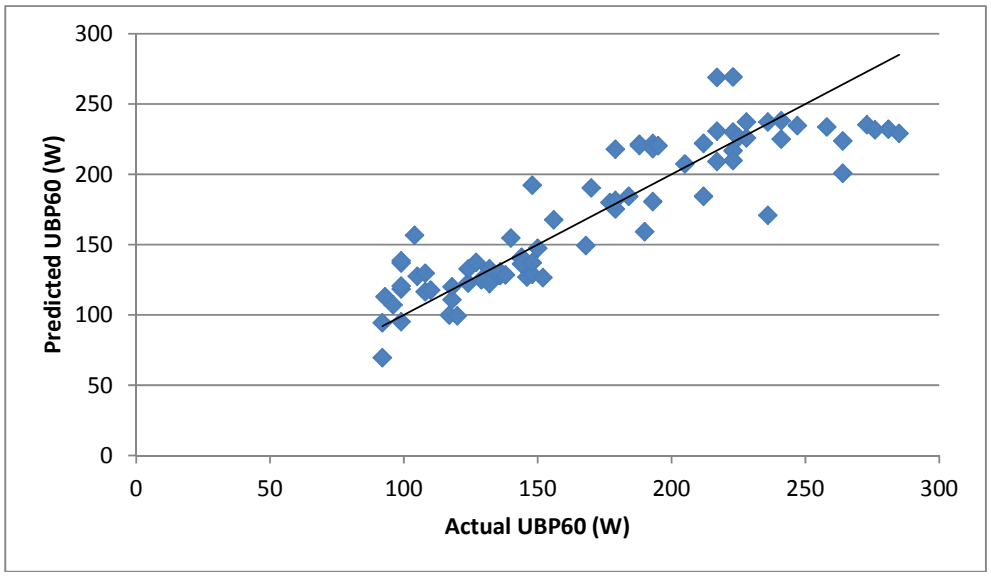


Figure 4.21. Scatter plot of actual UBP_{60} vs. predicted UBP_{60} for Model 50 using SVM-RBF

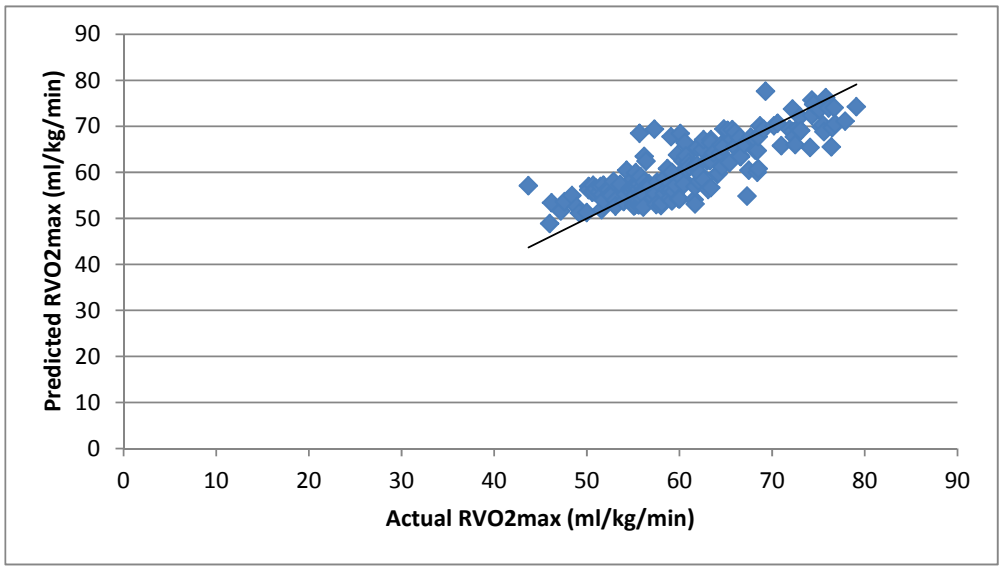


Figure 4.22. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 57 using SVM-RBF

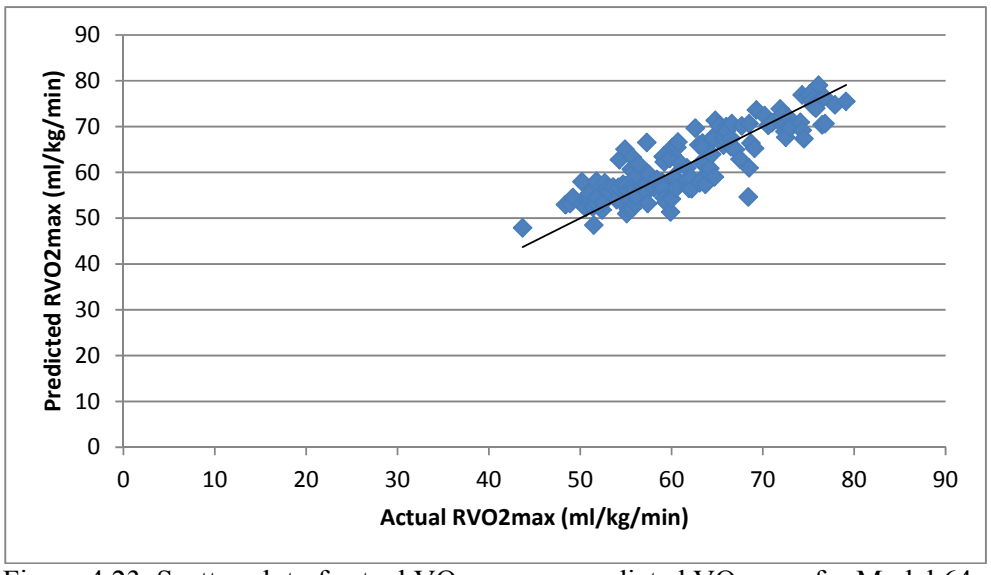


Figure 4.23. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 64 using SVM-RBF

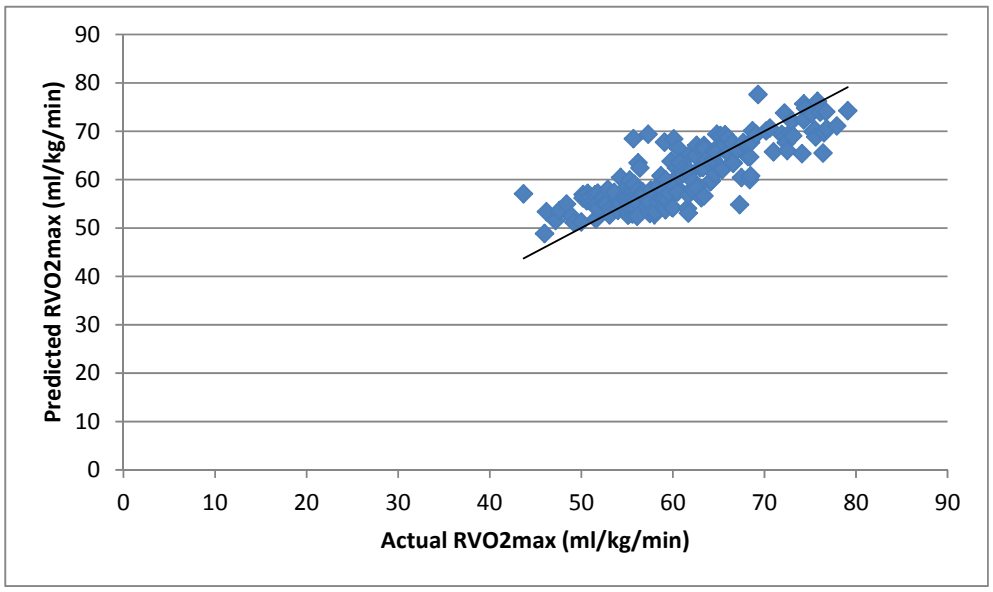


Figure 4.24. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 71 using SVM-RBF

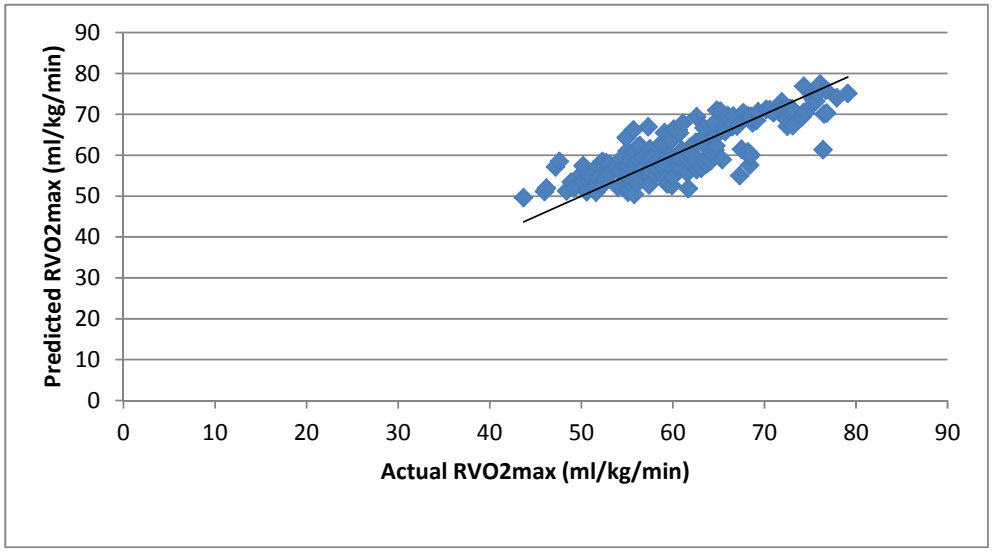


Figure 4.25. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 78 using SVM-RBF

5. CONCLUSION

In this thesis, numerous UBP and VO_2max prediction models for cross-country skiers have been developed using different data sets and combinations of the predictor variables protocol, age, gender, height, weight, BMI, HR, HRLT and exercise time. Different regression methods (i.e. SVM-RBF, SVM-Linear, MLP and MLR) have been applied on the prediction models. By using 10-fold cross validation on the data sets, the performance of the models has been evaluated by calculating *R*'s and *SEE*'s. The results show that UBP and VO_2max of cross-country skiers can be predicted with reasonable error rates.

Considering the results obtained, one can reach several conclusions. First of all, SVM-RBF-based prediction models show better performance (i.e. higher *R* and lower *SEE*) than the models developed by other regression methods. The order of the regression methods for prediction of UBP and VO_2max, from the best to the worst, is SVM-RBF, MLP, SVM-Linear and MLR. Due to the non-linear characteristics of UBP and VO_2max, linear regression methods yield higher *SEE*'s for prediction. On the other hand, linear regression methods yield faster results for prediction.

Inclusion of the "protocol" and "BMI" attributes in the models increases the error rates of prediction both for UBP and VO_2max. Error rates related to the prediction of UBP_{60} are always lower than that of UBP_{10} because of the high standard deviation of UBP_{10}.

This is an initial study to show that UBP of cross-country skiers can be predicted using regression methods. Future work can be performed in a number of different areas. Other regression methods such as generalized regression neural networks, radial basis function neural networks and tree-boosting can be used for prediction of UBP. Different feature selection algorithms can be combined with regression methods to identify the relevant and irrelevant features for prediction of UBP of cross-country skiers.

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CURRICULUM VITAE

Shahaboddin DANESHVAR was born in Tabrız-Iran, in 1982. He completed the elementary education at Modares, Tabriz. He went to Sema high school. He graduated from the department of Computer Engineering, Islamic Azad University, Tabriz, at 2011. He started MSc program at the department of Computer Engineering since 2012 with Assoc. Prof. Dr. Fatih Akay. He is interested in music, computer science, drawing and studying psychological books.